Peer Effects and the Gender Gap in Corporate Leadership: Evidence from MBA Students*

Menaka Hampole Francesca Truffa Ashley Wong

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Abstract

Women continue to be underrepresented in corporate leadership positions. This paper studies the role of social connections in women's career advancement. We investigate whether access to a larger share of female peers in business school affects the gender gap in senior managerial positions. Merging administrative data from a top-10 US business school with public LinkedIn profiles, we first document that female MBAs are 24 percent less likely than male MBAs to enter senior management within 15 years of graduation. Next, we use the exogenous assignment of students into sections to show that a larger proportion of female MBA section peers increases the likelihood of entering senior management for women but not for men. This effect is driven by female-friendly firms, such as those with more generous maternity leave policies and greater work schedule flexibility. A larger proportion of female MBA peers induces women to transition to these firms where they attain senior management roles. Qualitative interviews reveal that some of the mechanisms behind these results include emotional support and information transmission. These findings highlight the role of social connections in reducing the gender gap in senior management positions.

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Hampole: Northwestern University, menaka.hampole@kellogg.northwestern.edu. Truffa: Stanford Graduate School of Business, ftruffa@stanford.edu. Wong: Stanford University, ashley.wong@stanford.edu.

1 Introduction

The glass ceiling—the barrier that females and minorities face in obtaining upper-level positions—has been enduring. Despite decades of progress in labor force participation and university enrollment, women remain underrepresented in top corporate leadership positions. For example, in the S&P 1500 companies, women make up 40% of the workforce but hold only 6% of CEO positions (Hindlian et al., 2018). This gender gap widens at each step of the corporate ladder (Lean In and McKinsey & Company, 2020). To the extent that managerial talent is equally distributed across genders, the underrepresentation of women in executive roles can be indicative of talent misallocation (Hsieh et al., 2016).[1] Due to the potential aggregate consequences of female underrepresentation in executive positions, understanding the barriers to advancement along the corporate pipeline is critical.

This paper studies whether access to a larger share of female peers in business school helps women reach leadership positions. Although a growing literature shows that social connections formed during business schools have long-lasting impacts on future career outcomes, little is known about how they affect the gender gap in leadership positions.[2] A priori, the effect of the gender composition of social connections is ambiguous. On one hand, women may benefit from information and support from same-gender peers. For example, female connections can provide women with gender-specific information on which firms are more supportive of women's careers and how to take advantage of female-friendly policies, such as maternity leaves and flexible work schedules. On the other hand, social connections created with men may be more beneficial, given that men are more likely to have larger networks and hold more powerful positions. As a result, the role of female peers in closing the gender gap in management is largely an empirical question.

Identifying the causal impact of female peers on management outcomes is empirically challenging. First, peers and networks are likely to be endogenous. Unobservable characteristics, such as extroversion, likely determine both the composition of an individual's

[1] Since executives have significant influence on firm performance, the loss of female talent along the corporate pipeline may translate into lower firm productivity (Bertrand and Schoar, 2003; Bloom and Van Reenen, 2007; Bloom et al., 2012; Rasul and Rogger, 2018). Beyond influencing their own firm's performance, female managers may act as role models and implement policies to reduce barriers for other women in the corporate sector (Beaman et al., 2009; Chattopadhyay and Duflo, 2004; Beaman et al., 2012; Bhalotra et al., 2017). Thereby, female leaders can contribute to a more gender diverse and inclusive corporate culture.

[2] Examples of career outcomes affected by higher education peers are firm choice, likelihood of entrepreneurship, and executive decisions (Gorshkov et al., 2021; Yang et al., 2019; Lerner and Malmendier, 2013; Shue, 2013).

network and their likelihood of attaining leadership positions. Second, answering this question requires data on long-run career trajectories with detailed information on managerial positions.

To address the first challenge, we leverage a quasi-experimental setting provided by the Master of Business Administration (MBA) program at a top U.S. business school. At the beginning of the program, school administrators quasi-randomly assign students into sections based on alphabetical order. Students in the same section take core classes together and form strong social ties. We exploit the exogenous variation in the gender composition of the sections to study the effect of female peers on the probability of achieving a senior management position.[3]

We address the second issue by building a novel dataset with CV information from public LinkedIn profiles. In addition to complete education and employment history, this dataset contains two key pieces of information. First, it has job titles which allow us to identify an individual's progression along the managerial pipeline. Detailed information on hierarchical positions *within* management is usually unavailable in commonly used employment panel data in the literature. Second, it contains the names of employers which enables us to merge in firm attributes that the literature has hypothesized to be important for women's career progression (Goldin and Katz, 2016; Hotz et al., 2018). Specifically, we use novel metrics of female-friendly characteristics from InHerSight.com, an online platform where female employees rate their companies. This data enables us to identify firms with work cultures and policies that aim to help women balance their work-family responsibilities and support their career advancement. Some examples of such policies include maternity leaves, flexible working schedules, and female mentoring programs.

In the first part of our analysis, we document new descriptive facts on the gender gap along the management pipeline. Although 96% of male and female MBA graduates enter management roles within the first fifteen years post-MBA, women are 24% less likely to hold *senior* management positions. This gender gap emerges as early as the first year after the MBA and persists for at least fifteen years.

Then, in the main analysis, we use the exogenous assignment of students into sections to document three key findings. First, we show that having a higher proportion of female section peers during the MBA increases women's advancement into senior leadership positions. A 4 percentage point, or 1 standard deviation (SD), increase in the share of female MBA

[3] We define senior management positions as Vice President (VP), Director, Senior Vice President (SVP), or C-level Executive.

students leads to an 8.4% increase in the probability of holding a senior management position for women in the first fifteen years after MBA graduation.[4] In contrast, there is no effect on male students. This overall effect is economically significant and translates into a 26% reduction in the management gender gap. We find suggestive evidence of nonlinear effects of female peers, indicating that female share may have decreasing marginal returns and that an increase in female students could be particularly beneficial for women in sections with the lowest proportion of female students. We show that this increase does not come from women switching industries. Interestingly, we find the largest effects in *male-dominated* industries, where women are underrepresented. These results suggest that female MBA peer networks are important in industries where women are more likely to face barriers in accessing informal networks in the workplace.

Second, we investigate how firm characteristics play a role in explaining our main results. We show that women are not more likely to move to smaller or lower-compensation firms, where it may be easier to reach higher positions on the corporate ladder. Instead, our results are driven by *female-friendly* firms, firms that are characterized by policies such as maternity leave and flexible working schedules.[5] We show that women with more female peers are more likely to be promoted into senior management at female-friendly firms and are more likely to transition into these firms. The effect on entries emerges six to ten years after MBA graduation, when women are most likely to have young children in the household.[6] These results suggest that the support of female peers may be more effective at a point in the career path when the gender gaps in the labor market start widening (Bertrand et al., 2010; Kleven et al., 2019).

Lastly, to provide additional insights into the underlying mechanisms, we conduct qualitative interviews of female MBA graduates in our sample. The interviews revealed that during their careers, women often experienced gender discrimination and faced additional challenges balancing their work and family responsibilities. Female peers helped them overcome these barriers by (i) providing emotional support, (ii) contributing to a less intimidating MBA academic environment that help build their confidence, (iii) giving gender-specific information on which firms can support women and strategies on how to take advantage of family-friendly policies, as well as (iv) providing job referrals. In ongoing work, we will empirically test the relative weight of each mechanism in a quantitative survey.

[4] A 4 percentage point increase along the female share distribution corresponds to 2.4 additional women and is also equivalent to moving from the 25^{th} (32%) to the 75^{th} (36%) percentile.

[5] We identify female-friendly firms using InHerSight, a data source with firm ratings by female employees.

[6] See Bertrand et al. (2010).

A counterfactual exercise shows that, even holding the total number of female students fixed, reallocating them such that they are in sections with at least 34% women would lead to between 2 and 5 additional female senior managers per graduating class (corresponding to a 2.4% to 8.4% increase).[7] Together, our findings show that the gender composition of MBA peers has important implications on the career outcomes of women.

Our study contributes to four strands of literature. First, our paper contributes to the large literature on gender differences in the labor market and their determinants (Olivetti and Petrongolo, 2016; Blau and Kahn, 2017). These studies have highlighted many potential explanations that, among many others, include differences in labor supply (Bertrand et al., 2010), family responsibilities (Kleven et al., 2019), preferences for risk and competition (Buser et al., 2014; Mas and Pallais, 2017; Wiswall and Zafar, 2014; Niederle and Vesterlund, 2007), and marriage market concerns (Bursztyn et al., 2017). Most closely related to our study is Bertrand et al. (2010) which also investigates the career outcomes of MBA graduates. Bertrand et al. (2010) show that a large gender gap in earnings of 60 log points emerges in the decade after graduation. We contribute to this literature by documenting that female MBA graduates are also less likely to be promoted and are increasingly underrepresented in management positions despite having similar educational backgrounds as their male counterparts. This is possible due to our novel dataset that allows us to identify individuals' positions along the managerial pipeline and follow their career progression over time. Moreover, we use the exogenous assignment of students to peer groups to show that the gender composition of MBA peer networks can be an important determinant of the gender gap in leadership positions.

Second, our paper also speaks to the large literature on the importance of networks and referrals for career outcomes (Granovetter, 1973, 1995; Montgomery, 1991; Hwang and Kim, 2009; Bayer et al., 2008; Schmutte, 2015; Beaman and Magruder, 2012; Burks et al., 2015). A large branch of this literature studies how referrals and homophily can lead to persistent inequality in the labor market (Calvo-Armengol and Jackson, 2004; Bolte et al., 2021; Friebel et al., 2021). Prior studies suggest that because men are more likely to be in positions of power, men are more likely to receive referrals that can help them advance in their careers, compared to women (Beaman et al., 2018; Zeltzer, 2020; Mengel, 2020; Lalanne and Seabright, 2016). However, this literature has abstracted from the role of firm characteristics. For example, although women may benefit from more referrals, the *type* of the firm to which they are referred may also matter. The results of this paper suggest

[7]Note that this exercise assumes non-linearities.

that women's networks may transmit valuable private information about which firms may be more supportive of women. In the MBA context, there are two related papers on the role of female peers on career outcomes. Yang et al. (2019) shows that MBA students' social networks predict first post-MBA placement into leadership positions. In line with our results, this paper suggests that female peers are especially important for women. They find that female MBA graduates strongly benefit from inner circles of predominantly female contacts, while this is not true for men. One mechanism Yang et al. (2019) highlighted is that women require gender-specific information that they can obtain from strong female connections. In another study, a concurrent working paper by Thomas (2021) uses a similar context and identification strategy as our paper but finds that an increase in the share of *male* students leads to an increase in the salaries of female students at graduation and a higher likelihood of working in male-dominated industries. We contribute to this literature by considering how the gender composition of MBA peers can affect women's advancement into senior leadership roles. We present new evidence on the persistent effect of MBA peers and the underlying mechanisms including firm choice on women's career progression for up to fifteen years post graduation.

Third, this paper contributes to a growing literature on female-friendly policies such as maternity leave, childcare, and flexible working schedules (Goldin and Katz, 2016; Mas and Pallais, 2017; Hotz et al., 2018; Patricia and Jessica, 2019). This literature investigates the role that workplace attributes play in the career divergence of women and men, with the onset of parenthood. We contribute to this literature by showing that one potential mechanism for how female peer networks can help women advance into senior management is by increasing the rate at which women enter these firms. Our results highlight that there may exist complementarities between the availability of these firm-level policies and the gender-specific information provided by female peers.

Finally, this paper relates to an extensive literature that studies peer effects in many settings including education, managerial decision-making, and entrepreneurship.[8] The most related papers in this literature study the importance of female peers on the decision to enter male-dominated fields for female students as well as their performance in these fields (Bostwick and Weinberg, 2018; Brenoe and Zolitz, 2020; Calkins et al., 2020; Goulas et al., 2018; Schneeweis and Zweimüller, 2009; Anelli and Peri, 2017). The results of these studies have largely been mixed. In some cases, more female peers can help women persist and

[8]For example, Epple and Romano (1998); Lavy and Schlosser (2011); Sacerdote (2001); Zimmerman (2003); Stinebrickner and Stinebrickner (2006); Lerner and Malmendier (2013); Hacamo and Kleiner (2017)

excel in Ph.D. STEM programs (Bostwick and Weinberg, 2018), whereas in other settings, more female peers lead female students to choose more female-dominated fields (Brenoe and Zolitz, 2020). We provide new evidence that having access to a larger network of female peers indeed helps women achieve leadership positions and do so in sectors that are traditionally more male-dominated such as finance and tech. Our study also has several unique features compared to this literature. First, in almost all cases, these gender peer effects papers focus on contemporaneous or short-term impacts on academic outcomes. Our paper shows that the networks formed during graduate school are not only sustained but also have important and persistent impacts on the careers of women in the decades after graduation. Second, unlike these studies that rely on cohort-variation in gender composition, our study identifies peer effects using exogenous variation generated from the assignment of students to section *within* the same cohort. This experimental setting allows us to more credibly identify the causal impact of peers. Finally, disentangling the underlying channels leading to peer effects is intrinsically hard. Our paper shed light on the mechanisms through a combination of qualitative and quantitative evidence.

The paper is organized in the following way. Section 2 describes the setting. Section 3 presents the data used in the analysis. Section 4 illustrates new descriptive evidence on the gender gap in managerial positions along the pipeline. In Section 5, we turn to the role of female peers in the gender gap in management. Within this section, we present the empirical strategy (Section 5.1) and the main results (Section 5.2). We then explore the role of female-friendly firms (Section 6). In Section 7, we investigate potential underlying channels through which female peers help women advance into management positions. We then discuss the implications of these results in terms of compensation in Section 8. Finally, Section 9 concludes.

2 Background

Our study focuses on the career outcomes of full-time 2-year MBA graduates from a top business school in the United States. This setting is particularly well-suited for studying the relationship between peers and the gender gap in management positions for three reasons. First, MBA graduates are well positioned to obtain managerial roles; a large part of the MBA curriculum trains students for these roles. Bertrand and Schoar (2003) and

Bhagat et al. (2010) both find that around 40% of CEOs hold an MBA degree.[9] Second, there is evidence that social networks formed during MBA programs have important effects on graduates' career outcomes after the MBA, including firm choice (Hacamo and Kleiner, 2020), entrepreneurship (Lerner and Malmendier, 2013), executive decisions (Shue, 2013), and compensation (Yang et al., 2019; Thomas, 2021). In fact, business schools often highlight peer networking opportunities as an important benefit of the educational experience (Zimmerman, 2019; Kalsi and Samuels, 2019). Finally, this setting allows us to exploit the exogenous variation in female peers due to the quasi-random assignment of students to sections, overcoming one of the key empirical challenges in the estimation of peer and network effects.

Each year, at the beginning of the program, incoming MBA students are quasi-randomly assigned to one of eight sections based on alphabetical order.[10] Each section has around 6 students. We define as peers the students that belong to the same section. Students that belong to the same section are required to take core classes together. Core classes represent around 20% of the MBA curriculum and are taken during the first year. In the second year, students can choose elective courses and thus may not necessarily be in the same classes as their section peers. Students are typically not allowed to change sections and faculty are not matched to sections based on section characteristics. The explicit aim of sections is to foster close ties and networking among peers. Prior studies and anecdotal evidence suggest that students form and maintain close bonds with peers in their section (Lerner and Malmendier, 2013; Hacamo and Kleiner, 2016, 2017). For this reason, it seems plausible that peers may affect managerial career outcomes.

The school aims to achieve balance over three characteristics: gender, undergraduate institution, and ethnicity. Therefore, the assignment is implemented by following the three steps: 1) students are assigned to eight sections in alphabetical order; 2) the balance across gender, ethnicity, and undergraduate institution is checked; 3) if some sections have a share of male students, white students, or students from a given university above a set threshold, students are randomly reassigned to hit the target. For this reason, the balance is not perfect and there is meaningful variation in the proportion of female peers across sections within

[9]The samples in Bertrand and Schoar (2003) and Bhagat et al. (2010) slightly differ. Bertrand and Schoar (2003) uses data from Forbes 800 files, from 1969 to 1999, and Execucomp data, from 1992 to 1999. Bhagat et al. (2010) uses the Execucomp database from 1992 to 2007.

[10]Specifically, the first student in alphabetical order is assigned to section 1, the second to section 2, and so on, until the eighth student is assigned to section 8. After that, the ninth student is assigned to section 1, the tenth to section 2, and so on.

the same graduating class as shown in Appendix Figure A1. We will exploit this variation to study the effects of gender composition on managerial career outcomes of MBA students. The average female share at the section level is 34% with standard deviation of 4 percentage points.[11] In Section 5.1, we show that the assignment of students to sections is as good as random.

3 Data

We combine four novel sources of data: (i) school administrative data to construct the gender composition of section-mates, (ii) LinkedIn data for CV information on the entire education and employment history, (iii) data on employers' characteristics from a variety of sources, and (iv) alumni survey data for additional information such as timing of childbearing. In this section we provide an overview of the data sources and how we merge them together. We provide additional details in Appendix Section A. Detailed information on the matching rate across all these datasets is in Appendix Section E.

3.1 Business School Administrative Data

Aggregate statistics on the number of students per MBA section by gender and race are provided by the university administrators. This data allows us to construct our treatment variable (i.e., share of female students per section) using the universe of MBA students from cohorts graduating between 2000 and 2018.[12]

For MBA students graduating between 2011 and 2018, we also have individual school administrative data with information on demographics, pre-MBA educational background including GMAT scores, academic outcomes, and information on first job placement.

[11] We computed these statistics residualizing the share of female students by the graduating class and adding back the mean. In our setting one standard deviation approximately corresponds to moving from the 25$^{\text{th}}$ (32%) to the 75$^{\text{th}}$ (36%) percentile. The proportion of female peers ranges from 19% at the 1$^{\text{st}}$ percentile to 45% at the 99$^{\text{th}}$ percentile.

[12] Note that data on section assignments come from the fall of the matriculation year. Students who transferred from the 1-year to 2-year program are not included in these statistics as they were not assigned a section when they matriculated.

3.2 LinkedIn Profile Data

Data on employment and education background for 2-year full-time MBA graduates who graduated between 2000 and 2018 are obtained from public LinkedIn profiles, a professional networking social media platform. The profiles provide CV information on full education and employment history. The data include names of employers, start and end dates of employment, job titles, job location, schools attended, degrees received and graduation dates. As is typical in resumes, individuals create new entries for each job position, even within the same firm. As a result, we are able to track promotion patterns both within and across firms. Using the start and end dates of each position, we parse the CV data to create a yearly panel. We define nonemployment periods as time periods during which we do not observe a job entry. In our analysis, we will focus on career outcomes from year 1 to 15 post MBA graduation.

Across all class years, we successfully match 77% of the full-time MBAs to their public LinkedIn profiles. Detailed information on the matching rate is in Appendix Section E.

Sample Restriction

In the final analysis sample, we further restrict to only MBA graduates who are currently based in the United States using the locality information on the LinkedIn profiles. There are two motivations for this restriction. First, we obtain the sample of LinkedIn profiles via web searches on the U.S.-based LinkedIn webpage. Because LinkedIn may not be as widely used in other countries as in the United States, individuals based outside of the U.S. with U.S. LinkedIn profiles may be a selected sample. Second, we are interested in the role of MBA networks on long-term career outcomes. These peer ties are likely stronger in the United States as a vast majority of graduates remain in the country. In addition, the role of networks may differ substantially across different countries with different labor market structures and cultural norms. Note that even though we focus on individuals based in the United States in our main analysis, the proportion of female peers assigned to their respective section is calculated using all classmates, including those who eventually will not work in the United States.

Gender

Information on gender is available for the graduating classes of 2011-2018 in the administrative dataset. However, we do not have administrative records for earlier cohorts, and, neither the alumni directory nor the LinkedIn data contains gender information. Therefore, we utilize a series of customized name-matching algorithms to identify the gender of the graduate by comparing the first name of the graduate to established names databases. [13] Extending this method to the most recent cohorts, 2011-2018, for which we have administrative records reveals that we are able to correctly identify the gender 96% of the time.

3.3 Firm Data

We collect firm-level information from a multitude of data sources. We linked this additional information to our individual-level dataset using the names of the organizations listed for each position on the LinkedIn CV data. First, we collected LinkedIn company profiles which provide information on the number of employees and industries.

Second, we complement our dataset with compensation data provided by Glassdoor.com. This dataset contains 10.5 million self-reported compensation records for 639,422 firms from 2006-2017 and has information on base annual compensation and additional compensation in terms of cash or stock bonus, profits sharing, sales and commission, and tips. Notably, we also have information on the gender and job position of the respondent, enabling us to construct measures such as the gender gap in compensation at the firm level for all employees and for managers specifically. We also utilize this dataset to estimate compensation for each individual by assigning each person to the average compensation level of the firm, gender, and job level (non-manager, first-level manager, or senior-level manager).[14]

Third, we collect information on female-friendly firms from three sources. Our primary dataset on female-friendly workplaces comes from the online platform, InHerSight.com. This platform contains crowdsourced data on firm policies that may be important for the careers of women. We obtain employee ratings on metrics that include work flexibility, parental leave policies, mentorship, and female representation in management. InHerSight also provides an overall star rating for female-friendliness for each firm. This star rating is constructed using all the metrics collected on the firm. We provide the full list of metrics and description of the indices in Appendix Section A.5.1. We define a firm to be female-friendly if it has an

[13] These include the U.S. Social Security Administration baby name data, the U.S. Census data in the Integrated Public Use Microdata Series, and census microdata from Canada, Great Britain, Denmark, Iceland, Norway, and Sweden from 1801 to 1910 created by the North Atlantic Population Project. We compare the first names of the alumni in our data to these databases using the R package, "Gender" (`https://cran.r-project.org/web/packages/gender/gender.pdf`). We consider a graduate to be female if at least two of these sources identify the name to be female. We verify the gender of unmatched alumni through web searches on various online sources such as news and social media platforms.

[14] Note that we do not disaggregate by year of the salary because the cell sizes over which the average compensation would be calculated become too small.

above median rating on InHerSight.[15] In addition to data from InHerSight, we also collect data on overall firm ratings and number of weeks of paid parental leave from another, but smaller, crowdsourced platform, FairyGodBoss.com.[16] Lastly, we also acquire data on female board members for the public companies listed on the Russell 3000 Index from 50/50 Women On Boards. We provide additional details on these measures of firm female-friendliness in Appendix Section A.5. In Appendix Section A.5.4, we explore the correlation among these multiple metrics to validate our primary measure of female-friendliness.

3.4 Survey Data

We also conducted a survey of a 10% random sample of male and female graduates from classes 2000 to 2015, excluding 2009. We collect information in four areas that the literature has highlighted as potential important factors in MBA graduates' careers (Bertrand et al., 2010; Goldin and Katz, 2016; Yang et al., 2019; Hacamo and Kleiner, 2020). These areas include (i) family background such as children and spousal income, (ii) job flexibility, (iii) networking and role of peers, and (iv) ambitions and self-confidence. Additionally, we obtain data on compensation across the entire career trajectory to gain information on the wage gender gap and measure the impact of female peers on this gap. The response rate is 30% for a total number of responses was 328.[17] Appendix Section A.6 provides additional information on the survey sample.

3.5 Definition of Managers

Our main outcome of interest is attainment of senior management roles. A unique feature of our CV dataset is the availability of exact job titles, which permits us to identify managerial positions based on keywords.[18] This type of information is typically not available in large-scale surveys or datasets such as the Census or administrative tax data, where all managerial

[15]We use the number of ratings to weight statistics related to InHerSight.

[16]Because InHerSight data is available for 1,416 firms in our sample compared to 439 firms in FairyGodBoss, our primary measure of female-friendliness is the InHerSight rating.

[17]This is similar to response rate in the literature for similar populations. For example, Bertrand et al. (2010) had a response rate of 31% for University of Chicago MBA graduates.

[18]We also use the job titles to classify job functions as job descriptions are often missing from profiles. In our analysis, we identify 17 broad function categories: Accounting, Administrative, Consulting, Customer Service, Finance, General Management, Human Resources, IT, Legal, Marketing, Operations/Logistics, PR/Communications, Product Management, Research, Sales, Strategic Planning, and Other. See Appendix Section B for details on how we define and identify job functions.

positions are often reported under a single code. Following the guidelines offered by Lean In and McKinsey & Company (2020), we use common keywords in the job titles to identify managers ("manager", "supervisor"), Directors ("director"), Vice Presidents ("VP"), Senior Vice Presidents ("SVP"), and C-level executives ("Chief X Officer"). These positions form the corporate management ladder, allowing us to trace the gender gap and the effect of female peers across the pipeline. Appendix Section C provides more details on how we constructed these managerial positions. In the rest of the paper, we will refer to: 1) managers as first-level managers; 2) any positions from director to C-level executives as senior-level managers.[19]

In Appendix Table A3, to provide evidence supporting our managers classification, we present summary statistics by each of these job titles using our survey data. As expected, firm hierarchy as measured on a 1-5 scale increases along the management pipeline. On average, first-level managers oversee 14 employees -including both indirect and direct reports- compared to over 500 employees for C-level executives. Weekly hours worked and compensation also increase with each level of management. In particular, first-level managers earn \$185,314 in annual compensation compared to over \$300,000 for VPs, SVPs and C-level executives.

3.6 Summary Statistics

Appendix Table A1 presents the summary statistics for demographics (Panel A) and pre-MBA background characteristics (Panel B) for the full sample and by gender. All statistics in this table are measured at the person-level.[20] In our full sample, 36% of students are female. 39% of MBA students have held a management position prior to the MBA. A smaller percentage of students (13%) have held a senior management position. Interestingly, there is no gender difference in management experience prior to the MBA, but there is a 21% gender difference in total compensation. Moreover 64% of male students compared with 61% of female students have worked in a male-dominated industry (finance, tech or consulting).

Appendix Table A2 presents the descriptive statistics for the set of academic outcomes

[19] In addition to managerial positions, we also identify founders and entrepreneurs using the keywords "Founder", "Owner" and "Self-employed." Note that in our analysis, we exclude founders from the management outcomes and instead analyze founders separately.

[20] Measures in Panel B come from the main LinkedIn dataset for our sample of full-time MBAs who graduated between 2000 and 2018, excluding class of 2009. Except for pre-MBA years of experience, the statistics are measured two to five years prior to MBA graduation, i.e. the three years prior to entry into the MBA program. For pre-MBA experience, we use the total number of years with work experience listed on the online profile for the ten years prior to the MBA.

measured at the person level (Panel A) and career outcomes at the person-year level (Panel B). During the MBA, male students have a higher overall GPA by 0.06 points and take 29% more finance classes as a proportion of all classes taken during the MBA.[21] 75% of graduates are in a management role while 43% are in a senior management role. Although women are equally likely to be in a management position, they are 14 percentage points, or 29.8% less likely to hold a senior management position. Additional summary statistics are provided in Appendix Section C.1.

4 Gender Gap in Corporate Leadership Positions

In this section, we document three new descriptive patterns for the gender gap in senior management positions among MBA graduates. We show that (i) female graduate are 24% less likely to hold senior management positions; (ii) this gender gap emerges immediately after the MBA and persists for at least fifteen years; (iii) women are 26% less likely to be promoted into senior management positions from first-level management.

First, we show that despite no gender differences in the entry rate into the management pipeline, a gender gap emerges at the senior management position level. In Figure 1, we show the likelihood of ever holding a management position at each of the seniority levels in the 15 years after MBA graduation for male and female graduates. Nearly all graduates (96%) of both genders have held a management position in the first fifteen years of their postgraduate career. However, a gender difference emerges when we consider each position of the senior management pipeline separately. Men are significantly more likely to attain one of the three senior leadership positions, VP or Director, SVP, and C-level executives. In Appendix Section F.2, we show that there is a substantial gender gap of 24% in senior management when we control for class fixed effects, year fixed effects and class interacted with year fixed effects. Controlling for gender differences in pre-MBA characteristics, firm characteristics, industry choice, and gaps in the employment history reduces this gender gap, but a 17.6% difference in likelihood of holding senior management positions remains unexplained. Given that there are no gender differences in overall management positions, these patterns suggest that, although female MBA graduates enter first-level management

[21] Previous work has found that the gender difference in finance courses can help explain the gender wage gap for MBA graduates (Bertrand et al., 2010).

positions, many of them do not advance into senior management.

Second, the gender gap in senior leadership positions emerges immediately post MBA and persists over time. Figure 2 plots the dynamics in the likelihood of holding any senior-level management position over the years since MBA graduation.[22] The figure points to a persistent gender gap in senior leadership positions that emerges at the outset of the post-MBA career and widens slightly over time. This suggests that women begin their careers in management positions at lower levels or in nonmanagement roles, and they do not catch up in the years post MBA. While 74% of men are holding a senior management position in year 15, only 59% of women are. In Appendix Figure A4, we shows that the gender gap in senior management is present in all industries with the largest gender gap in consulting, and the smallest in healthcare.

Third, we show that women are less likely to transition into senior-level management positions from first-level management positions. In Figure 3, we plot the 5-year transition probabilities for first-level managers into either a senior management position, non-management position, nonemployment, or remaining in the same position.[23] We show that 57% of men in first-level management roles transition into a senior management role in the next five years compared to 43% of women. This difference is significant at the 5% level and suggests that women are not being promoted at the same rate as men. Women are also more likely to move to non-management positions or nonemployment, suggesting lower persistence in managerial positions. However, the gender gap in persistence is unlikely to explain the gender differences in representation in senior management positions given the smaller magnitudes of the transitions into lower positions.

Together, these descriptive results show female MBAs are significantly less likely to hold senior leadership positions even though they are just as likely as male MBAs to enter management. They begin their careers in lower levels compared to men and once in the management pipeline, they are less likely to move into higher positions. As a result, a gender gap in senior management appears at the outset of the post-MBA career persists and does not close over the next fifteen years.

[22]Note that these results are unconditional on employment.

[23]Nonemployment is identified based on gaps in the reported work history.

5 The Role of Female Peers in the Gender Gap in Management

We now investigate a potential determinant of the gender gap in senior management: the gender composition of MBA peers. We begin by describing the empirical strategy for identifying the causal impact of female peers on management. Using the exogenous assignment of students into sections, we show that a 4 percentage point increase in the share of female peers increases women's likelihood of attaining a senior management position by 8.4%. We show that this effect is concentrated in male-dominated industries and we provide suggestive evidence of non-linearities.

5.1 Empirical Strategy

Empirical Challenges

The literature has highlighted three main empirical challenges in the identification of peer effects.[24] Our setting is particularly well-suited to deal with these challenges. First, our estimates are unlikely to suffer from selection bias because of the exogenous assignment of MBA students to sections. Second, we are able to isolate peer effects from the potential confounding effect of common shocks because our treatment variable is based on a pre-determined characteristic, gender. In fact, the exogenous assignment makes it unlikely that common shocks are correlated with this pre-determined characteristic. Finally, our estimates do not suffer from reflection bias because we model the outcome only as a function of an individual's background characteristics and peers' average background characteristics. Appendix Section G provides a more detailed discussion on the empirical challenges in the identification of peer effects and their implications in our context.

Empirical Specification

We estimate peer effects using a linear-in-means model in which holding a senior management position depends on own gender and the proportion of female students among MBA section peers. Following Bertrand et al. (2010), we use a pooled sample in which we include all observations of an individual such that each observation refers to an MBA graduate in a

[24]See, for example, Manski (1993); Sacerdote (2011, 2001); Brock and Durlauf (2001); Moffitt (2001); Lerner and Malmendier (2013); de Paula (2017); Charles et al. (2018); Caeyers and Fafchamps (2021).

given post-MBA year. Specifically, we use the specification:

$$\begin{aligned} y_{ikct} = &\alpha_1 \overline{FemaleShare}_{-i,kc} \times Male_i + \alpha_2 \overline{FemaleShare}_{-i,kc} \times Female_i + \\ &+ \alpha_3 Female_i + \sum_{j=0,1} (\delta_c + \phi_t + \omega_{ct}) \times I(Female_i = j) + X_{ikct}\gamma' + \epsilon_{ikct} \end{aligned} \tag{1}$$

where y_{ikct} is the outcome of interest for individual i in section k from graduating class c in year since graduation t. $\overline{FemaleShare}_{-i,kc}$ is the proportion of female peers of i in section k and graduating class c. $Female_i$ is a dummy that takes value 1 for female and 0 for male, while $Male_i$ is a dummy that takes value 1 for male and 0 for female. The specification also includes a series of class fixed effects (δ_c), year fixed effects (ϕ_t), class-by-year fixed effects (ω_{ct}), and their interactions with the gender dummy. This allows us to isolate only within cohort variation in female share. Therefore, by exploiting within-gender-within-class variation, our coefficients are not affected by changes in the gender composition of the program over time.

The term X_{ikct} represents a series of individual and section-level control variables. Because the section assignment algorithm aims to achieve balance on gender, undergraduate institution, and ethnicity, we control for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking. Hereafter, we will refer to this as stratification variable. Unfortunately, we are unable to control for ethnicity due to lack of data availability. We also include pre-MBA characteristics that are predictive of becoming a senior manager: any senior management experience dummy, and having worked in finance for precision.[25] All individual level-characteristics are interacted with the gender dummy. Lastly, we include a series of section-level controls that account for differences across sections to bolster the interpretation of these results. As observed in Table A1, gender differences exist across many pre-MBA characteristics. As a result, a larger share of female peers may capture alternative channels such as having a larger share of peers from more female-dominated industries. Following the methodology employed by Lerner and Malmendier (2013), we control for section-level characteristics that are significantly correlated with share of women in the section: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role,

[25]To identify the predictors, we regress a dummy for holding a senior management position on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and pre-MBA characteristics using the pooled sample. The results of this regression are presented in Appendix Table A4.

US locality, white, and foreign.[26,27,28] We cluster standard errors at the section level for all of our specifications.[29]

The exogenous variation in female peers allows us to interpret our two coefficients of interest, α_1 and α_2, as causal. α_1 and α_2 represent the total effect of having more section female peers on the outcome variable for men and women, respectively. α_3 captures the gender gap in outcomes conditional on controls.

Identification Assumption and Randomization Test

In order to identify the causal effect of peers, our empirical strategy relies on the idea that the distribution of female share across sections is as good as random. In our setting, because the assignment was done by the university, we implement randomization tests to show that the assignment of students is as good as random. A natural first attempt is to test whether the gender of the student is correlated with the female share of the section. However, as first highlighted by Guryan et al. (2009) and recently expanded upon by Caeyers and Fafchamps (2021), there is a systematic negative correlation between the characteristic of the individual and her peers due to the fact that an individual cannot be her own peer when assignment is done without replacement.[30] Caeyers and Fafchamps (2021) refers to this bias as the "exclusion bias." As a result, we implement two alternative randomization tests proposed by Guryan et al. (2009) and Caeyers and Fafchamps (2021), respectively, that take this bias into account.[31]

[26]In Appendix Table A7, we present section-level summary statistics for different pre-MBA characteristics. This table reports the coefficients from bivariate regressions of female share on each of the specified section characteristics controlling for class fixed effects. Nine characteristics are significant at the 5% level. These include share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, US locality, white, and foreign. Note that Lerner and Malmendier (2013) use a forward stepwise selection process to choose their final section-level controls, but because we have much fewer characteristics than in their case (16 vs. 68), we utilize linear regressions for this purpose.

[27]Share of white and foreign are computed using statistics aggregated at the section level from administrative data between 2000 and 2018. However, since we have individual administrative data only for years 2011 to 2018, in computing these shares we can not leave out the individual as we do for all other shares.

[28]In Section L.1, we show that our estimates are robust to alternative sets of controls.

[29]We cluster at the section level because there may be common shocks that affect the entire section leading to correlation in the outcome variable within the section. However, as we discuss in the identification section, due to exogenous assignment and the focus on a predetermined characteristic, the common shocks would not bias our estimates. We show in Section L.1 that our results are robust to clustering at the class level.

[30]When class fixed effects are included, the exclusion of an individual from the pool of potential peers creates a systematic negative correlation between the individual's characteristics and that of her peers.

[31]Caeyers and Fafchamps (2021) is a generalization of the methodology proposed by Jochmans (2020).

The first randomization test is proposed by Guryan et al. (2009) and has been widely implemented in the peer effects literature (Carrell et al., 2009; Sojourner, 2013).[32] The rationale behind this test is that, after controlling for the leave-out mean of female share in the class, the section-level leave-out mean should be precisely estimated and not significantly different from zero. Table 1 shows that the section-level leave-out mean is not significant either when using the full sample of cohorts between 2000 and 2018 (Columns 1-2) or when we restrict to the sub-sample of cohorts between 2011 to 2018, for which we have administrative data (Columns 3-4). It also does not depend on the inclusion of covariates.

The second randomization test, proposed by Caeyers and Fafchamps (2021), is an alternative to the test proposed by Guryan et al. (2009). Caeyers and Fafchamps (2021) provide an exact formula to quantify the magnitude of the exclusion bias in our setting with unequal section and class size, assuming homoskedastic errors. Instead of adding a bias correction term in the estimating equation as in Guryan et al. (2009), Caeyers and Fafchamps (2021) show that the randomization test can be implemented by netting out the asymptotic exclusion bias first.[33] We present the results of the randomization test in Table 2 for the full sample (Columns 1-2) and for the cohorts between 2011 and 2018 (Columns 3-4).[34] The coefficient for female share is insignificant across all specifications with or without the main set of controls used in our baseline specification.[35] [36] The results of this test and the previous one suggest that the distribution of female share is in fact as good as random in both samples and they provide strong support for the validity of our empirical strategy.[37]

For this reason, we decided to report the results from using the approach in Caeyers and Fafchamps (2021). Results from Jochmans (2020) are available upon request.

[32]See Appendix Section H for details on this randomization test.

[33]See Appendix Section I for details on this randomization test.

[34]Following Caeyers and Fafchamps (2021), the estimation is done clustering at the class level. In Section L.1, we show that our results are robust to clustering at the class level.

[35]Note that when implementing this test with covariates, we first partial out additional regressors using the methodology described by Caeyers and Fafchamps (2021).

[36]As additional evidence, in Appendix Table A5 we conduct the same randomization test when the dependent variable is being a female student from a top 20 undergraduate institution in Column (1), being a female student with senior managerial experience in Column (2), being a female student with experience in finance in Column (3). Consistently to the previous results, we do not find any significant effect. Similarly, in Appendix Table A6, we present the coefficients from regressing female share on the female dummy and the three variables that predict the probability of becoming senior manager (coming from a top 20 undergraduate institution, having experience as senior manager, having worked in finance). We can not reject the null of the joint significance of these coefficients.

[37]In Appendix Section J, we provide an additional test to show that the within-class peer-gender variation is as good as random. Specifically, following the methodology in Bietenbeck (2020), we compare the actual distribution to a simulated within-class distribution of female share. Appendix Figure A5 shows no statistically significant difference between the actual and the simulated distribution, providing supporting

5.2 Main Results

In this section, we first present the main results on the effect of female peers on MBA graduates' likelihood of holding senior managerial positions. We then provide an interpretation of the effect size, provide suggestive evidence of nonlinear effects of female peers, and show that this effect is concentrated in male-dominated industries. We conclude showing a series of robustness checks and empirical tests to support our resultss.

Main Regression Results

Figure 4 shows the binned scatterplot of the relationship between female peers and the probability of becoming a senior manager. Both the outcome and female share have been residualized by the full list of controls in our main specification (1). Importantly, this figure shows the within-gender and within-class variation. Each dot represents the average likelihood of holding a senior management position within 10-percentile bins of female share. We find a strong positive causal relationship between the exposure to female peers and the likelihood of attaining a senior managerial position for female graduates and no effect for male graduates.

Table 3 Column (1) reports the corresponding estimates. We find that a 4 percentage point (1 SD) increase in the share of female MBA students leads to a 8.4% (=0.822*0.04/0.391) increase in the probability of holding a senior management position on average across the fifteen years after MBA graduation.[38] In contrast, there is no effect on male students. This is perhaps surprising given that an increase in female share would imply a decrease in male share. On one hand, to the extent that a larger network of male peers matters for male students' career outcomes, we would expect a negative impact for males. On the other hand, female peers may provide useful information across genders and be beneficial for male graduates as well. The null result suggests that access to a larger network of same-sex MBA peers is much more beneficial for women than for men. This is consistent with the "old boys' club" hypothesis in that male MBA graduates may have easier access to networking opportunities at their firms and may not need to rely on their MBA networks as much for their career advancement (Cullen and Perez-Truglia, 2019).[39]

evidence of as-good-as-random assignment of the share of female peers.

[38]A 4 percentage point increase along the female share distribution corresponds to 2.4 additional women and is also equivalent to moving from the 25^{th} (32%) to the 75^{th} (36%) percentile.

[39]In Appendix Section K.3 we explore the effect of female peers on additional outcomes.

Interpretation of the Effect Sizes

In this section, we interpret the economic magnitude of our main results and its implications in terms of gender gap in leadership positions. In Table A47, we showed that female MBA graduates are 12.8 percentage points (24%) less likely to reach senior leadership positions compared to 54% of men. Our results in Table 3 suggest that a 4 percentage point (1SD) increase in the share of female MBA students leads to a 3.3 percentage point increase (8.4%) increase in the probability of holding a senior management position. This is equivalent to a 26% (=3.3/12.8) reduction in the gender gap on average across the fifteen years after MBA graduation. These effects are economically large and consistent with the hypothesis that same-gender peers play a key role in the career advancement of women.[40]

Dynamic Effects of Female Peers

In our baseline estimation, we estimated equation (1) pooling all the years since graduation. In order to understand the dynamics of when female peers help female MBAs transition into senior management positions, we estimate equation (1) separately for each post-MBA year. Figure 5 plots the coefficients α_1 and α_2's from equation (1) which represent the total effect of female share on men and women, respectively.[41] The dynamic patterns show an increase in the probability of holding a senior management position over time since graduation.[42] We find that a 4 percentage point (1SD) increase in female share leads to a 7.7% (=0.046/0.593) increase in the likelihood of holding a senior-level management position for women fifteen years after graduation.

Effects Along Management Pipeline

We next decompose the effects on senior managerial positions into individual positions along the management pipeline: Directors and Vice Presidents (VP), Senior Vice Presidents (SVP), and C-level executives. We find that our main results on senior managers are driven by entries of women into VP and director positions. Appendix Table A10 presents the overall

[40]There is limited evidence of the effect of gender representation on women's advancement into leadership positions. One paper that studies a similar outcome to ours is Dalvit et al. (2021). This paper investigates the effect of board quotas on female senior managers in the context of a 2011 French reform. We find that the magnitude of our results corresponds to an increase in female board members from 10 percent to 24 percent.

[41]Regression estimates are presented in Appendix Table A8.

[42]The estimates are more imprecise towards the end of the sample period as the number of observations fall as more recent cohorts drop out of the sample.

effect on each management position using the pooled sample.[43] We find that a 4 percentage point (1SD) increase in female share leads to a 9.6% (=0.029/0.304) increase in the likelihood of holding a director or VP position for women during the first fifteen years from graduation (Column 1). On the contrary, we find no effect for SVPs and C-level executives in Columns (2) and (3), respectively. The null effect on SVPs and especially C-level positions should be interpreted cautiously given that the vast majority of our sample has not reached the level of seniority to hold these positions yet.

Nonlinear Effects of Female Peers

Are there nonlinearities in the effects of female peers on women's likelihood of becoming a senior manager? Increasing female share may have a larger impact in sections with a lower share of female students. In order to test this hypothesis, we use a one-knot spline regression, which allows us to identify significant changes in our coefficients of interest along the distribution of female share. Specifically, we modify equation (1) by interacting the main coefficients of interest with an indicator variable for being in a section with above-median share of female peers (34%) across all classes.[44] Table 4 reports the total effect of female peers for sections with female share below and above the median. While the estimated effect is larger for women in sections below the median, we can not reject equality between the two coefficients. This null result is potentially due to a lack of statistical power. These findings, nonetheless, provide suggestive evidence that female peers are particularly beneficial for women in sections with a lower female share, pointing to the presence of decreasing marginal returns of additional female students. The presence of decreasing marginal returns would also help explain the lack of effect for men.

Attachment to the Corporate Pipeline

We showed that female peers have a positive effect on the probability of becoming a senior manager. We now explore whether our results on senior management are driven by an increase in the attachment to the corporate pipeline as measured by employment and career breaks, entry rate into the managerial pipeline, and likelihood of self-employment. Appendix Table A25 shows that there are no effects on employment or career breaks, suggesting that this channel cannot play a key role in explaining our results.[45] Then, we test

[43]The effects over time for probability of holding each management position are plotted in Appendix Figures A8, A9, and A10 for Director and VP, SVP, and C-level executives, respectively.

[44]We provide additional details on the estimation in Appendix Section L.

[45]Note that, while we do not have childbirth information, we are able to infer employment and career

the hypothesis that female peers encourage women to enter management positions (including first-level positions), which in turn would lead to a subsequent increase in senior management. Appendix Table A26, however, shows no effect on holding any managerial position. Finally, we ask whether female peers may increase promotion rates into senior managerial positions by reducing the likelihood of self-employment.[46] There is suggestive evidence that women may use self-employment as a way to work part-time or lower hours and have a better work-life balance (Bertrand et al., 2010). If female peers help women, who otherwise would have moved into self-employment, remain attached to their firm, this may explain the increase in female senior management. In Appendix Table A27, we find no significant effect on self-employment. Appendix Section M.1 provides more details on these results.[47]

Senior Managers, Firm Size, and Firm-Level Compensation

We then investigate whether female peers have an effect on the type of firms where female senior managers work in terms of size and firm average compensation. In Appendix Tables A11 and A12, we show that women are not more likely to become senior managers in firms of a different size or with a different level of average compensation. Moreover, we find that female peers do not induce women to move to smaller firms or low-paying firms, where it may be easier to reach higher positions along the corporate ladder (Appendix Tables A13 and A14).[48,49] Consistent with these findings, in Appendix Table A17, we show that our main results on senior management are robust when we estimate equation (1) controlling for firm size and firm average compensation.

Male-Dominated Industries

Interestingly, in this section we show that the increase in senior managers is driven by higher rates of promotion for women in male-dominated industries with no corresponding

breaks based on the dates listed on CV. We define a career break as a gap between the end and start dates of two consecutive positions of at least a 3-month.

[46]Our definition of senior manager does not include entrepreneurs.

[47]Also notice that, since we do not find an effect on being an entrepreneur, our results do not depend on whether we include entrepreneurs in our definition of senior managers.

[48]More details on this analysis are provided in in Appendix Section K.1.

[49]In Appendix Section K.1, we also show that the increase in female senior managers is not associated with lower Profit and Loss (P&L) responsibilities. Having Profit and Loss (P&L) responsibility involves monitoring the net income after expenses for a department or an entire organization, with direct influence on how company resources are allocated. These roles have been shown to be essential for promotions into top executive positions.

shifts in employment towards these industries.[50] Specifically, Appendix Table A16 reports the estimates for holding a senior management position in a male-dominated industry (Column 1) and in a female-dominated industry (Column 2). We show that a 4 percentage point (1SD) increase in female share leads to a 12% (=0.024/0.201) increase in the probability of becoming a senior manager in a male-dominated industry. On the contrary, we find no effect on the probability of becoming a senior manager in a female-dominated industry. The difference between the two coefficients of interest is significantly different at the 3% level.[51]

However, Column (3) of Appendix Table A16 shows that there is no significant effect on entries into male-dominated industries.[52] [53] These results provide suggestive evidence that the increase of senior managers in male-dominated industries is driven by higher promotion rates of women in these industries. [54]

5.3 Robustness Checks

We present a series of robustness checks to provide supporting evidence that our results credibly identify the causal effect of female peers on senior positions for women.[55]

Missing Data and Alternative Samples

First, we provide evidence that our results are not driven by unmatched observations or the restrictions to our sample. In Appendix Table A19, we investigate whether unmatched observations from each of the datasets are systematically correlated with female peers. We report the regression results from estimating equation (1) where the dependent variable in

[50] As shown in Appendix Figure A3, there exists substantial gender variation in industry choice. Male-dominated industries are consulting, tech, and finance. Female-dominated industries are consumer goods and healthcare.

[51] See Appendix Table A28 for the p-values from the tests of pairwise differences across the two specifications.

[52] Given that the coefficient is imprecisely estimated, we provide two additional pieces of evidence against an effect on industry choice. First, in Appendix Table A29, we present the analogous results for each industry separately. We find no overall effect of female peers on industry choice. Second, Appendix Figure A14 shows the dynamic effects for entries in male-dominated industries. Consistent with our pooled results, we do not find a significant effect in any of the post MBA years included in our analysis.

[53] Notably, this result stands in contrast to prior gender peer effects papers that find a significant relationship between female peers and the choice of female students to enter in male-dominated fields of study such as STEM (Brenoe and Zolitz, 2020). The difference in this setting may result from the fact that MBA graduates enter the program with five years of work experience on average and, as a result, are less influenced by their peers in the choice of industry.

[54] More details and additional results are provided in Appendix Section .

[55] Additional details are provided in Appendix Section L.1.

each column is a dummy if the individual is matched to the specified dataset.[56,57] We do not find a correlation between female share and being in the sample in any case. This provides strong evidence that selection into the sample cannot explain our results.

We also conduct a series of robustness checks using alternative definitions and samples and re-estimating equation (1) for senior management. Results are summarized in Appendix Figure A12 and in Appendix Table A22. Specifically, we show that the main result is robust when: (i) we use an alternative nonemployment measure where we assume that all the time periods up to 2019 are nonemployment spells (Column (2)); (ii) we restrict the sample to people we can follow throughout the fifteen years post-graduation (Column (3)); (iii) we drop from the sample outliers sections (i.e., sections with a proportion of female students in the first and last percentile of the female share distribution) (Column (4)); (iv) we include entrepreneurs in the definition of senior managers (Column (5)); (v) we restrict the analysis to the observations for which we have information on industry and level of female-friendliness of the firm, as defined in Section 3.3 (Columns (6) and (7)).

Placebo Tests

Second, we run two placebo tests. First, following the methodology described in Athey and Imbens (2017), we conduct a randomization test in which we randomly re-assign students to sections within the same class.[58] In Appendix Figure A11, we plot the distributions of the placebo treatment effects for men and women, respectively. The vertical lines indicate the actual coefficients we estimated using the true section assignment. The true effect for men falls within the distribution of placebo effects, consistent with the null effect on men that we find in our main results (Section 5.2). On the contrary, the estimated true effect for women is much larger than any of the placebo effects, providing supporting evidence that the estimated impact of female peers on women's probability to become senior managers is unlikely to have occurred by chance.

Second, if female share in each section is exogenous, it should have no effect on our

[56]Note that we do not include controls beyond gender, class and year fixed effects, because additional information is not available for unmatched individuals.

[57]Because this analysis requires microdata and we do not have individual data for the full census of MBA graduates prior to 2011, we use the alumni directory records as a proxy for the sample universe in Columns (1) and (2). That is, missing dummy equals 1 if in the alumni directory records and 0 otherwise. In Columns (3) and (4), we use the matched LinkedIn and administrative data to conduct the analysis for the 2011-2018 cohorts.

[58]The re-assignment is performed without replacement and using uniform probability. We conduct this re-assignment 1,000 times and, in each iteration, we estimate our coefficient of interest from equation (1) for our main outcome variable, probability of holding a senior management position, for both men and women.

outcome variable in the years prior to the MBA, when peer groups have not been formed yet. Appendix Table A20 shows the coefficients from regression (1) estimated separately for up to three years before the start of the MBA program. We find no consistent evidence of an effect of female share on female future graduates, supporting our identification strategy.

Alternative Empirical Strategies

Finally, we show that our results are robust to a series of alternative empirical strategies. First, in Table A21, we show that our estimates are robust to alternative sets of controls. Column (1) reports the estimates from the baseline specification. In Column (2), we only control for class fixed effects, year fixed effects class-by-year fixed effects, as well as their interactions with a female dummy. Then, in Column (3), we also include stratification variables as controls. Lastly, in Column (4), we add individual level-characteristics as described in Section 5.1.[59] Across all specifications, we show that female peers have a significant and positive effect on career advancement of women with no corresponding effects on men.

Second, we show that our estimates are robust to clustering at the class level.[60] Appendix Table A23 shows the coefficient of interest from estimating equation (1) when clustering at the section level (Column(1)) and when clustering at the class level (Column(2)). The two clustering levels lead to almost identical results.

Finally, we show that our results are robust when we use a conditional logit model instead of OLS. Appendix Table A24 reports the coefficients from our main specification in Column (1) and from the logistic specification in Column (2). We find that with this alternative model the effect of female peers is positive and significant at the 3.4% level. The marginal effect is 0.477 which translates into a 4.9% increase in the probability to be a senior manager for a 4 percentage point (1SD) increase in the female share distribution.

6 Female Peers and Female-Friendly Firms

Our results in the previous section show that female peers help women advance into senior corporate leadership positions. The increase in female senior managers is not driven by an increase in the attachment to the corporate pipeline. Also, our results are concentrated in

[59]Note that for all of the controls we include, we also include missing indicators and all of their interactions with a female dummy.

[60]The reason for this check is that, although in our main empirical strategy we cluster at the section level as in Guryan et al. (2009), when we implement our second randomization tests (Section 5.1) we cluster at the class level to follow the approach in Caeyers and Fafchamps (2021).

male-dominated industries, where women may face additional barriers in accessing informal networks and therefore may rely more on their MBA female peers. In this section we explore the role of firm characteristics and show that our results are driven by female-friendly firms.[61]

In Section 5.2, we showed that the increase in female senior managers cannot be explained by changes in firm size or firm-level compensation. However, firms may differ along other dimensions that can be beneficial for women's career advancement. In particular, a growing literature has documented the importance of female-friendly workplaces for the labor market outcomes of women (Claudia, 2014; Goldin and Katz, 2016; Hotz et al., 2018). To identify female-friendly firms, we leverage novel crowdsourced employee ratings data from InHerSight.com.[62] We classify a firm as female-friendly if it has an above-median rating. The ratings from InHerSight capture female employees' perception on metrics such as generosity of the maternity leave policies, flexible work schedules, and professional support. Note that female-friendly firms are present in both male- and female-dominated industries.[63]

We first present descriptive results on the role of female-friendly firms in explaining the gender gap in senior management. We show that the gender gap in management narrows over time in female-friendly firms but widens in non female-friendly firms. We then investigate whether female MBA peers have a stronger effect in female-friendly firms. We find that the increase in senior management for female MBAs is concentrated in female-friendly firms. This increase is driven in large part by more women joining these firms later in their career. This suggests that female MBA peers may provide women with key support at a critical moment of their careers, when they are more likely to have young children.

Descriptive Dynamics of the Gender Gap in Senior Management in Female-Friendly Firms

In Figure 7, we plot the probability of holding a senior management position over the years since graduation by gender and female-friendliness of the firm. The figure shows that regardless of the type of firm, women are less likely to be senior managers than their male counterparts. We also find limited evidence that the career paths for men differ across these types of firms. However, even though female MBAs are equally as likely to hold senior

[61] Female-friendly firms are firms that provide policies to help women balance their work-family responsibilities and support their career advancement.

[62] Additional details provided in Appendix Section A.5.1.

[63] Interestingly, Appendix Figure A18 shows that the proportion of female-friendly firms is higher in the three male-dominated industries (tech, finance, and consulting). We find the lowest share of female-friendly firms in consumer goods, which is the industry with the highest female representation in terms of employees.

management positions in both female-friendly and non female-friendly firms at the beginning of the post-MBA career, a divergence occurs beginning eight years after graduation. Female MBAs are increasingly more likely to hold senior management positions in female-friendly firms, shrinking the gender gap. In contrast, in non female-friendly firms, women are much less likely to progress compared to both men and women in female-friendly firms. The timing of this divergence between the two types of firms coincides with the moment in the life-cycle when female MBAs are likely to have young children in the household.

This descriptive pattern is consistent with the hypothesis that female-friendly firms help women balance their work-family responsibilities (Hotz et al., 2018). Availability of female mentoring and sponsorship programs may also provide women with the necessary support to advance in their careers (Blau et al., 2010).[64] Furthermore, in addition to female-friendly policies, these types of firms may also have a work culture that is more supportive of women and helps them transition into management positions. This result provides suggestive evidence that female-friendly workplaces may play an important role in helping women advance in their careers.

Senior Managers in Female-Friendly Firms

The descriptive results suggest that female MBA graduates are more likely to progress in female-friendly firms. We next explore whether female peers help women gain senior leadership positions in these firms. Table A34, Column (1), shows that female peers significantly increase women's likelihood of becoming a senior manager in a female-friendly firm, while they do not affect the probability of becoming a senior manager in a non-female-friendly firm (Column (2)).[65] The difference between the two coefficients is significant with a p-value of 0.014.[66] In Appendix Section M.3, we validate these results using alternative measures of female-friendliness from other data sources and find consistent results.

In Section 5.2, we showed that our results are concentrated in male-dominated industries and provided suggested evidence that this increase comes from an increase in promotions within these industries and not a shift across industries. A natural follow-up question is whether within male-dominated industries the increase in senior managers can be explained

[64]We note that female-friendly firms may differ along other dimensions that would explain this pattern. However, we show in Table A31 that there is no significant difference in firm size or firm average compensation between female-friendly and non-female friendly firms. Instead, as expected, female-friendly firms are characterized by a larger proportion of female board members and more weeks of paid maternity leave (although the difference is not significant for the latter).

[65]In Appendix Figure A16, we show the dynamic effects of these results.

[66]See Appendix Table A28.

by female MBA graduates shifting into more female-friendly firms. In Appendix Section M.4, we show that when we restrict to male-dominated industries, the effect is driven by female-friendly firms, suggesting that the increase in female senior managers is driven by women moving to female-friendly firms within male-dominated industries.

What features of female-friendly firms are driving our results? Recall that the female-friendly measure comprises 18 metrics. We create six standardized indices by grouping these 18 underlying metrics following six broad topics: 1) gender equal opportunities; 2) work schedule flexibility; 3) professional enrichment; 4) fair compensation; 5) family friendliness; 6) workplace culture. In Appendix Figure A15 and Appendix Table A32, we report the analogous results for firms that are above or below the median in each of the component indices.[67] The results suggest that women are most likely to be senior managers in firms with higher work schedule flexibility and family-friendliness, such as those providing more generous maternity leave policies. We also find positive effects for firms with greater professional enrichment, better workplace culture, and gender-equal opportunities. In contrast, we do not find a differential effect for the index capturing whether a firm is perceived to have fair compensation. This aligns with earlier results that find no impacts on firm-level compensation.

Entries vs. Promotion

What explains the increase in senior managers in female-friendly firms? This effect may be driven by a combination of new entries in female-friendly firms and higher promotion rates in these firms. We present evidence that entries play a nontrivial role in these results.

In Table A34, Column (3), we show that there is no effect on likelihood of working at a female-friendly firm, although the estimate is very imprecise.[68] However, this null result masks considerable heterogeneity along the career path. In Appendix Figure A17, we plot the likelihood of working in a female-friendly firm over time since graduation. There is an increasing effect on women joining female-friendly firms beginning six to seven years after MBA graduation. This period coincides both with an increase in female senior managers in female-friendly firms as shown by our descriptive analysis in Figure 7, and with the years when women are more likely to have childcare responsibilities. Specifically, in our survey

[67]We describe how we aggregate the components of the female-friendly firm metrics into six broad categories in Appendix Section A.5.1.

[68]We also do not find much evidence along the specific dimensions of female-friendly firms in Appendix Table A33.

data, we find that 50% of graduates have children three to seven years after graduation.[69]

Moreover, while we have documented an increase in entries into these firms, these results do not rule out the possibility that female peers may also increase the rate of promotions of women at these firms. To provide suggestive evidence on this effect, in Appendix Table A34, we study the likelihood of becoming a senior manager conditioned on working in a female-friendly firm or a non female-friendly firm. We find a positive impact for women in female-friendly firm, suggesting that promotion can play a role. However, we acknowledge that these results are endogenous to women's decision to join different types of firms and should be interpreted with caution. [70] It is beyond the scope of this paper to quantify the relative magnitudes of the selection and promotion channels for senior management, but we believe it would be an interesting avenue for future research.

7 Quantitative and Qualitative Evidence on Mechanisms

Our results show that access to a larger proportion of female peers help women advance into senior management positions. In Section 6, we show that female peers encourage women to join female-friendly firms where they are more likely to be promoted. In this section, we explore the mechanisms underlying the treatment effects by presenting quantitative and preliminary qualitative evidence from interviews with 45 female MBA alumni. The women were randomly sampled from our study, stratified by year of graduation and if they were ever a senior manager. We oversampled those that attained senior management positions to understand how female peers may have affected their career trajectories.

The interviews were conducted by a sociology Ph.D. student using an in-depth narrative approach following the methodology employed by Bergman et al. (2019). During the inter-

[69]This pattern of childbirth is also similar to the results found by Bertrand et al. (2010) in their study of University of Chicago MBA graduates.

[70]Note that we cannot rule out that these results may also capture the impact of female managers on these female-friendly firm policies. The InHerSight data is collected in 2021, which in some cases is many years after the women in our sample have been promoted to senior management. Potentially female peers increase women's likelihood of becoming senior managers and in turn, these female managers implement policies that make the firm more female-friendly today. However, as we show in Appendix Table A35, the results are very similar when we restrict to only large firms with over 5000 employees, where any single manager may be less influential. This suggests that this explanation is unlikely to explain these results.

view, we asked the respondent to describe her career path after the MBA, the challenges she may have faced in the workforce and how she dealt with these challenges. We also inquired about the role of their MBA female peer network.

The rest of this section is structured as follows. First, we provide descriptive evidence from the qualitative interviews on the challenges female MBAs faced in their careers. Then we provide evidence on four key mechanisms that were frequently highlighted by the interviewees: (i) emotional support, (ii) improved academic environment, (iii) gender-specific information, and (iv) job referrals.

7.1 Challenges Faced by Female MBAs

Our qualitative interviews with female MBA alumni highlighted a series of challenges that women face during their career progressions. First, nearly all in our sample mentioned that they have experienced some form of gender bias or discrimination. A large share report having difficulties forming relationships with male leaders or felt they did not have "fair shot" to be promoted. For example, a female MBA alumna from the class of 2015 said "When working at this startup, there seems to be an aversion to females, because [...] it was a very clique-y company and the top clique was all white males who had worked at the same company before... It seemed to appear that a lot of the males who were less qualified and had worked in the business less time were getting promotions faster and were getting bigger check raises than the females."

In addition, women also reported they were often treated unfairly compared to their male counterparts. Many women felt they were often criticized for attributes that are not related to their work performance such as being "too emotional" or "not assertive enough". For example, a respondent described "I was in a discussion with some sales leaders, and we are trying to have a [...] discussion about where the problems are in the sales organization or what needs to be done. And after that meeting, [...] there were questions about the tone I was taking in that meeting. Which I don't fundamentally have proof that it was based on a sexist assumption. *But I don't know too many men who are chastised for their tone coming out of leadership level meetings where we're just trying to have a business discussion.*"

Second, women were challenged by the lack of family-friendly policies. In several cases, the companies where women worked offered no official maternity leave policies or had policies on paper but no official procedures in place. One woman came back from maternity leave and found out that the firm "had divided [her] job into three roles" and was told to "figure out what [her] role is the day [she] got back from maternity leave."

Finally, even with family-friendly policies in place, women in our interviews had difficulties balancing motherhood and career concerns. For some, their firms continue to place high time demands and expect new mothers to work "14 hours a day". At the same time, mothers are juggling family responsibilities. As one woman describes, "we've been out of school for seven years. People have had their kids [...] Gone are the days where you're working 80 hour weeks, and you really need to find a job that just allows for more flexibility." Learning how to navigate this period was pivotal:

> "I would say, though, probably the most dramatic thing was when I had kids. It was at a time where my career was really at a defining moment. I was trying to get these manager director jobs. I had to take different roles, get put out of opportunities, because I was, you know, anticipating being out of the workforce... And then, when I went back in to interview [and told them about the baby], they were not as interested in me, which was really disappointing."

Overall, the women in our interviews faced considerable and gender-specific challenges in their post-MBA careers. Everyone we interviewed agreed that they faced additional difficulties that men in similar careers did not, suggesting that female peers may have a comparative advantage in helping women navigate these challenges given their shared experiences. We explore four potential mechanisms in the following sections.

7.2 Four Key Mechanisms

Our interviews reveal that female peers provide an important support system for women. 90% of our interviewees declared that they rely more on women in their network than on men. To identify the main mechanisms through which female peers support women's career advancement, we first fully read interview transcripts and listed the specific mechanisms emerging from them. Then we coded the frequency of each mechanism. Our interviews reveal four key mechanisms: 1) Emotional support; 2) Improved academic environment; 3) Gender-specific information; 4) Job Referrals.

7.2.1 Emotional Support

One of the most frequent form of support that women mention in our interviewers is emotional support from other female peers. More specifically, they talk about how women create an "organic community" and support each others by "sharing stories" and "experience." For example, a female MBA alumna from the class of 2011 said "There's [a] shared lived experience[...] We are women in industry who are finding the same challenges and factors that are influencing our advancement, regardless of industry[...] We can understand those things and how we navigate them make sense to me."

This larger emotional support system could be critical to keeping women motivated throughout their career progression as well as to raise women's self-confidence. The literature has identified self-confidence and ambitions as possible drivers of the gender gap in male-dominated fields and managerial positions (Carlana, 2019; Rosenthal et al., 1996; Rosenthal, 1995; Kirkpatick and Locke, 1991). Given that we do not have any measure of self-confidence and ambition in our current datasets, we plan to collect survey data on these outcomes to test this channel more directly.[71]

7.2.2 Improved Academic Environment

In addition to emotional support, women mention that having more female peers in sections contributes to a "less intimidating" and "safer environment" during the MBA. This academic environment helps women feel more comfortable when participating in class and asking questions. For example, a female MBA alumna from the class of 2015 said "I feel like having a good group of women with whom you could be in small groups just makes it *less intimidating* [to ask questions]. I think that it's just a safer environment, and so I think if you have that, from the beginning, like in your study groups [...], *it would just be a skill that you would learn in life.*"

One hypothesis is that such environment may help women succeed academically during the MBA, raising their human capital, and propelling them to success later in their careers.[72]

[71]Specifically, following previous reports on the gender gap in the managerial pipeline (Lean In and McKinsey & Company, 2015, 2019), we ask MBA alumni whether they would like to become top executives and in which position (such as non-managerial, low-level manager, director, VP, SVP, c-suite, not working) they expect to be in five and ten years. Finally, to measure their self-confidence, we ask whether they feel comfortable tackling any work-related challenge that comes their way. To measure professional skills we ask MBA alumni whether they negotiated any component of the compensation, whether they asked and/or obtained a raise and/or a promotion.

[72]While the evidence for the MBA context is more sparse, a large literature in education has documented the importance of peer effects for educational achievement and skills development (Duflo et al., 2011; Brenoe and Zolitz, 2020; Sacerdote, 2001). Given that female students represent roughly 30% of each graduating class, more female peers may lead to greater participation and engagement in the classroom, leading to higher academic achievement that can translate into higher job performance or better credentials for MBA recruiting.

In particular, Bertrand et al. (2010) have shown that higher GPA and coursework in finance during the MBA are key predictors for postgraduate earnings and this may reflect higher job seniority and greater management responsibilities. To test this hypothesis, in Appendix Table A40, we use the school administrative dataset for the classes of 2011 to 2018 to study whether a higher proportion of peers that are female leads to a change in the GPA or the share of finance classes during the MBA.[73] We do not find any evidence that female peers affected the academic performance of female students or their course load in finance. Therefore, it seems unlikely that the increase in senior managers is driven by changes in academic preparation as a result of more female peers.

However, this null effect does not rule out that women who study in a more gender balanced section developed more self-confidence as a result of the more gender-diverse environment. Moreover, this environment may have helped women acquire professional skills, such as negotiation skills that can translate into better performance on the job and increasing likelihood of promotion. These effect may not necessarily translate into higher MBA academic performance. Given that these hypotheses can not be tested with our current professional platform data directly, we are currently collecting survey data on these outcomes.

7.2.3 Gender-Specific Information

We also find evidence that female peers help women in their careers by providing two types of gender-specific information. The first set of information relates to firm benefits and culture. For example, a female alumni from the class of 2015 said "If I receive an offer, I'm comfortable talking to a [female] friend [...] I'd ask how maternity leave works or generally what the female community looks like and what the support is. *I probably wouldn't ask those questions [to a hiring manager] in the off chance the person uses this as a red flag.*"

Second, female peers provide useful general information on how to balance work-life responsibilities and female-related policies. They provide advice on what kinds of firm attributes women should focus on while searching for a job and how to take advantage of family-related policies. A female alumni from the class of 2015 said "I was one of the first people at an earlier stage company [...] to actually have kids [...] and so they had no idea what parental leave looks like [...]. I had to write up a document that scopes who to contact and how to leave my projects to other people. *I talked to several females from the [MBA] community who had already gone through this cycle, just to learn exactly how they*

[73] Appendix Table A41 present the results for GPA by field.

left things."

The information we obtained from our interviews is consistent with the literature. Female peers have been shown to provide private career information that may be more relevant for women than for men (Yang et al., 2019). In male-dominated settings, women may provide more credible and gender-specific information about topics such as navigating job cultures, managing relationships, and balancing work-family responsibilities (Sandberg and Scovell, 2013; Saloner, 1985). This is particularly true regarding firm-level information such as firm culture, hiring and promotion strategies, and family-friendly policies.

7.2.4 Job Referrals

Finally, many women mentioned referrals as a critical form of support that they received from their business school peers, especially during the first years post MBA. For example, a female alumni from the class of 2009 said "Early on getting out of school, one of my first good jobs out of business school I got through a classmate...in the first [few] years, there was a lot more leaning on classmates in the network to find potential hires." Although in many occasions women mentioned receiving referrals by both male and female peers, referrals from female peers seem to become more relevant when women search specifically for firms with a more female-friendly environment - such as firms with female leadership. This suggests that female peers may have a comparative advantage in referrals to specific types of firms.

Although, we cannot observe referrals directly in the data, we are able to provide supporting evidence for this channel using our CV data. Specifically, we use the dyadic analysis employed by Schmutte (2015) and Bayer et al. (2008) to test empirically whether MBA graduates are more likely to work in the same firm of a classmate if they are from the same section and have the same gender. The idea is that if female peers are important for referrals, then female students should be relatively more likely to work in the same firm of a female peer than that of a male peer. To investigate this effect, we form a new dyadic dataset in which all MBA graduates are matched to all possible classmates of the same graduating year. We then estimate the following:

$$\begin{aligned} y_{i,j} = {} & \alpha_1 SameSection_{i,j} \times BothMales_{i,j} + \alpha_2 SameSection_{i,j} \times BothFemales_{i,j} \\ & + \alpha_3 SameSection_{i,j} + \alpha_4 BothMales_{i,j} + \alpha_5 BothFemales_{i,j} + \delta_c + \phi_f + u_{i,j} \end{aligned} \tag{2}$$

where $y_{i,j}$ is a dummy that takes value 1 if the MBA graduate i and his or her classmate

j work in the same firm. $SameSection$ is a dummy that takes value 1 if i and j were in the same section. $BothMales$ is a dummy that takes value 1 if i and j are both men and, analogously, $BothFemales$ is a dummy that takes value 1 if i and j are both women. We also include class fixed effects, δ_c, and firm fixed effects, ϕ_f. Because sections are exogenously assigned, α_3 measures the causal effect of having a connection from the same section on the likelihood of joining the same firm. The parameters of interest are α_1 and α_2 which provides the differential effect of coming from the same section and being both men or both women, respectively. We use two-way clustering and cluster at both the individual and firm level.

Table 6 shows the results from estimating equation (2). We find that same-gender job networks formed through sections are significantly more important for women. Specifically, female MBA graduates are 0.1 percentage points more likely to be working in the same firm of a female section peer. This effect represents a 19% increase compared to the baseline. The coefficients for being from the same section and both males or mixed-gender peers are small and insignificant, suggesting that being from the same section boosts probability of entering the same firm only for women. This indicates that female graduates may benefit more from same gender peers than male graduates.

In Section 6, we found evidence that female peers encourage women to enter female-friendly firms. If job referrals and gender-specific information are mediators of the effect of female peers, we should find stronger effects in female-friendly firms. In Appendix Table A39, we present the results of an analogous analysis in which we interact the coefficients in equation (2) with an indicator of whether a firm is female-friendly. We find that the effect of same-gender female section peers is driven by female-friendly firms, supporting our qualitative evidence that female peers introduce women to this type of firms.

These results provide suggestive evidence that one important channel for women's advancement into senior management is access to job referrals through MBA female peer networks. This interpretation is consistent with our results. For example, in our earlier findings, we show that women are more likely to transition into female-friendly firms later in their career, around the time of childbirth and raising young children.

8 Discussion: Implications for the Gender Gap in Compensation

The effect of female peers on women's advancement into senior management positions may have implications in terms of compensation. In this section we show that female peers affect non-base compensation (i.e., cash or stock bonus, profits sharing, sales and commission, and tips). Although we cannot directly observe compensation in the data, we are able to infer expected compensation based on firm, job title, and gender using our Glassdoor dataset[74].

Descriptive Dynamics

We begin this analysis by documenting the evolution of the gender gap in imputed compensation. Figure A22 shows the descriptive dynamics of base and total annual imputed compensation in the five years before and fifteen years after the MBA by gender. We also plot the ratio of total to base compensation. We show that a gender gap in compensation is present among MBA graduates prior to the MBA and increases over time, as was also documented by Bertrand et al. (2010).[75] We find that non-base compensation can explain the vast majority of the total gender gap in compensation. In fact, in year 15, while the gender gap in base compensation is around 18%, the total compensation gender gap reaches 35%.[76] Moreover, 15 years after MBA graduation, bonuses represent 20% of women's compensation compared to almost 30% of the total compensation for men.[77]

Female Peers and Compensation

We now provide evidence on the effect of female peers on the gender gap in imputed compensation. In Appendix Table A42 Column (1), we find a positive effect, although not significant, on total annual compensation.[78] In Columns (2) and (3) we decompose total compensation into its base and non-base components. We find that the positive effect on compensation is

[74]See Section 3.6

[75]Note that the imputed compensation likely underestimates the true compensation as discussed in Section 3.6 and shown in Appendix Figure A2.

[76]In year 15, average base compensation is $154,702.4 for men and $127,003.5 for women. Average total compensation is $282,375.3 for men and $184,372.9 for women.

[77]This result is consistent with the findings in Hirsch and Lentge (2021) that shows a large part of the gender wage gap among managers in Germany can be explained by bonus compensation. In Appendix Section N, we provide evidence of what explains the gender gap in imputed compensation.

[78]Values are reported in thousands of dollars.

driven by the non-base component which displays a positive and significant increase. The coefficients slightly decrease, but remain significant once we control for the manager category (non-manger, first-level manager, senior manager) fixed effect.[79] This suggests that female peers contribute to the reduction of the gender gap in non-base compensation by helping women both achieve higher managerial positions and obtain higher wages once they achieve senior positions. One potential explanation is that female peers may provide useful negotiation skills, especially related to the bonus components which, as we show in Figure A22, explains most of the gender gap in compensation. Although investigating the mechanisms behind these results is beyond the scope of this paper, this section provides suggestive evidence that female MBA peers may play a role in women's compensation.

9 Conclusion

Despite decades of progress, women continue to be underrepresented in top corporate leadership positions, a phenomenon widely referred to as the glass ceiling. This paper provides new causal evidence on whether access to a larger network of female peers during the MBA provides a pathway to senior leadership positions for talented women. We combine school administrative records of MBA graduates from a top U.S. business school with novel CV data from a large professional social media platform. Importantly, these data contain detailed job positions allowing us to track individuals' progression along the management pipeline.

Descriptive results show that female MBA graduates are 24% less likely to hold a senior management position (VP, Director, SVP, or C-level) even though they are equally as likely as male MBAs to enter the management pipeline. They begin their careers in lower levels compared to men and they are 26% less likely to be promoted into higher positions from first-level management.

Using the exogenous assignment of MBA students to sections, we show that increasing the proportion of female section peers raises the probability of holding a senior management position for female MBA graduates. However, there is no effect for male MBA graduates. A 4 percentage point (1SD) increase in female share reduces the gender gap in senior management by 26%. These results are not driven by an increase in the attachment to the corporate pipeline and they are concentrated in industries where women are underrepresented (i.e., male-dominated industries) and where women may rely more on their female MBA peers.

[79] See Appendix Table A43.

Moreover, we show descriptively that over time women are more likely to advance into senior management positions in female-friendly firms, narrowing the gender gap. In contrast, we observe a widening gender gap in non female-friendly firms. We find that a larger share of female peers increases the rate at which women become senior managers specifically in female-friendly firms. This effect is largely explained by a higher entry rate in the later part of women's careers, when they are likely to have children. Lastly, we show that these effects on female-friendly firms can explain the increase in senior managers in male-dominated industries. In these industries, women are more likely to move to female-friendly firms, where they attain senior management positions.

In the final part of the paper, we present quantitative and qualitative evidence on the challenges women faced in their careers and how female peers supported them to overcome the barriers they encountered. Interviews with female MBA alumnae revealed that female peers help women navigate potential gender discrimination and balance family and work concerns through key mechanisms such as emotional support and gender-specific information. One important way female peers support the careers of women is by providing information on which firms are more supportive of women's careers and how to take advantage of female-friendly policies, such as maternity leaves and flexible work schedules.

Our findings suggest that access to a larger network of female peers can raise women's likelihood of attaining senior leadership positions. In particular, female-friendly workplaces appear to play an important role in women's career advancement.

The results of this study have important implications for policies that aim to address the underrepresentation of women and minority groups in corporate leadership. Although the formalization of a policy recommendation is beyond the scope of this paper, we provide a back-of-the-envelope calculation to illustrate that the gender compositions of MBA peers can play a key role in the reduction of the gender gap in leadership positions. Specifically, extrapolating our results on non-linearities from Section 5.2 and assuming no change in the total number of female students admitted in our MBA program between 2000 and 2018, we show that reallocating female students to reach a 34% female share across all sections, would lead to 2 to 5 additional female senior managers per graduating class (corresponding to a 2.4% to 8.4% increase), depending on the assumptions made.[80] While we recognize the

[80]Given 60 students per section, 34% female students per sections, and a total of 144 unique section-by-class peer groups between 2000 and 2018, the total number of female students between 2000 and 2018 is given by $144 * 60 * 0.34 \approx 2938$. From our summary statistics, we know that 39% of female graduates are senior managers, for a total of 1146 (=2938*0.39) female senior managers. We compare the real distribution of female share across sections in our data with a counterfactual where all sections are assumed to have 34%

limitations of this calculation, it illustrates that the gender composition of MBA peers can have important impacts on the gender composition of top executive positions.

of female students. We then compute the differential effect of female peers between the baseline allocation and the new allocation. To do that, we use the coefficients from the one-knot spline in Table 4. In this table, we find that female peers have a positive but non-significant effect in sections with a share of female students above the median (34%). To compute our lower bound we interpret this coefficient as zero marginal effect. This leads to 42 additional female senior managers or an average of 2 additional female senior managers per graduating class. Instead, for our upper bound, we assume that the effect of female peers above the 34% cutoff is equal to the value of the coefficient. This leads to 96 additional female senior managers or an average of 5 additional female senior managers per graduating class. Note that, for classes with an overall female share below 34%, we assume that female students are allocated such that a section reaches 34% female share before starting filling out the following section, until all female students in the class are allocated.

References

Anelli, M. and G. Peri (2017, 10). The Effects of High School Peers Gender on College Major, College Performance and Income. *The Economic Journal 129*(618), 553–602.

Athey, S. and G. W. Imbens (2017). The econometrics of randomized experiments. *Handbook of Economic Field Experiments 1*, 73–140.

Bayer, P., S. Ross, and G. Topa (2008). Place of work and place of residence: Informal hiring networks and labor market outcomes. *Journal of Political Economy 116*(6), 1150–1196.

Beaman, L., R. Chattopadhyay, E. D. R. Pande, and P. Topalova (2009). Powerful Women: Does Exposure Reduce Prejudice? *Quarterly Journal of Economics 124*(4), 1497–1540.

Beaman, L., E. Duflo, R. Pande, and P. Topalova (2012). Female Leadership Raises Aspirations and Educational Attainment for Girls: A Policy Experiment in India. *Science 335*(6060), 582–586.

Beaman, L., N. Keleher, and J. Magruder (2018). Do job networks disadvantage women? evidence from a recruitment experiment in malawi. *Journal of Labor Economics 36*(1), 121–157.

Beaman, L. and J. Magruder (2012, December). Who gets the job referral? evidence from a social networks experiment. *American Economic Review 102*(7), 3574–93.

Bergman, P., R. Chetty, S. DeLuca, N. Hendren, L. F. Katz, and C. Palmer (2019, August). Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice. Working Paper 26164, National Bureau of Economic Research.

Bertrand, M., C. Goldin, and L. F. Katz (2010). Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. *American Economic Journal: Applied Economics 2*, 228–255.

Bertrand, M. and A. Schoar (2003, 11). Managing with Style: The Effect of Managers on Firm Policies*. *The Quarterly Journal of Economics 118*(4), 1169–1208.

Bhagat, S., B. J. Bolton, and A. Subramanian (2010). Ceo education, ceo turnover, and firm performance. *SSRN Working Paper*.

Bhalotra, S., I. ClotsFigueras, and L. Iyer (2017, 08). Pathbreakers? Women's Electoral Success and Future Political Participation. *The Economic Journal 128*(613), 1844–1878.

Bietenbeck, J. (2020). The long-term impacts of low-achieving childhood peers: Evidence from project star. *Journal of the European Economic Association 18*(1), 392–426.

Blau, F. and L. Kahn (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature 55*(3), 789–865.

Blau, F. D., J. M. Currie, R. T. A. Croson, and D. K. Ginther (2010, May). Can mentoring help female assistant professors? interim results from a randomized trial. *American Economic Review 100*(2), 348–52.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2012, 11). Does Management Matter? Evidence from India *. *The Quarterly Journal of Economics 128*(1), 1–51.

Bloom, N. and J. Van Reenen (2007, 11). Measuring and Explaining Management Practices Across Firms and Countries*. *The Quarterly Journal of Economics 122*(4), 1351–1408.

Bolte, L., N. Immorlica, and M. O. Jackson (2021). The role of referrals in inequality, immobility, and inefficiency in labor markets. *Working Paper*.

Bostwick, V. K. and B. A. Weinberg (2018, September). Nevertheless she persisted? gender peer effects in doctoral stem programs. Working Paper 25028, National Bureau of Economic Research.

Brenoe, A. A. and U. Zolitz (2020). Exposure to More Female Peers Widens the Gender Gap in STEM Participation. *Journal of Labor Economics 38*(4), 1009–1054.

Brock, W. and S. Durlauf (2001). Interactions based models. *Handbook of Econometrics 5*, 3299–3380.

Burks, S. V., B. Cowgill, M. Hoffman, and M. Housman (2015, 02). The Value of Hiring through Employee Referrals *. *The Quarterly Journal of Economics 130*(2), 805–839.

Bursztyn, L., T. Fujiwara, and A. Pallais (2017, November). 'acting wife': Marriage market incentives and labor market investments. *American Economic Review 107*(11), 3288–3319.

Buser, T., M. Niederle, and H. Oosterbeek (2014). Gender, competitiveness, and career choices. *The Quarterly Journal of Economics 129*(3), 1409–1447.

Byham, T. M. and E. Fraser (2021). P&l responsibility: Why women don't get to the c-suite.

Byrne, J. A. (2020, Mar). Is the mba job market about to crash?

Caeyers, B. and M. Fafchamps (2021, March). Exclusion bias in the estimation of peer effects. Working Paper 22565, National Bureau of Economic Research.

Calkins, A., A. J. Binder, D. Shaat, and B. Timpe (2020). When sarah meets lawrence: The effect of coeducation on women's major choices.

Calvo-Armengol, T. and M. O. Jackson (2004). The effects of social networks on employment and inequality. *American Economic Review 94*(3), 426–454.

Carlana, M. (2019). Implicit stereotypes: Evidence from teachers gender bias. *The Quarterly Journal of Economics 134*(3), 1163–1224.

Carrell, S. E., R. L. Fullerton, and J. E. West (2009). Does your cohort matter? measuring peer effects in college achievement. *Journal of Labor Economics 27*(3), 439–464.

Carty, J. P. (2017). Thesaurus-of-job-titles. `https://github.com/johnpcarty/Thesaurus-of-Job-Titles`.

Charles, K. K., E. Hurst, and M. J. Notowidigdo (2018). Housing booms and busts, labor market opportunities, and college attendance. *American Economic Review 108*(10), 2947–2994.

Chattopadhyay, R. and E. Duflo (2004). Women as policy makers: Evidence from a randomized policy experiment in india. *Econometrica 72*(5), 1409–1443.

Claudia, G. (2014, April). A grand gender convergence: Its last chapter. *American Economic Review 104*(4), 1091–1119.

Cullen, Z. B. and R. Perez-Truglia (2019, December). The old boys' club: Schmoozing and the gender gap. Working Paper 26530, National Bureau of Economic Research.

Dalvit, N., A. Patel, and J. Tan (2021). Intra-firm hierarchies and gender gaps. *Labour Economics*, 102029.

de Paula, A. (2017). Econometrics of network models. *in B. Honore, A. Pakes, M. Piazzesi and L. Samuelson (Eds.), Advances in Economics and Econometrics: Theory and Applications: Eleventh World Congress, Econometric Society Monographs*, 268–323.

Duflo, E., P. Dupas, and M. Kremer (2011). Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya. *American Economic Review 101*(5), 1739–1774.

Duflo, E. and E. Saez (2003, 08). The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment*. *The Quarterly Journal of Economics 118*(3), 815–842.

Epple, D. and R. E. Romano (1998). Competition between private and public schools, vouchers, and peer-group effects. *The American Economic Review 88*(1), 33–62.

Frankel, B., S. Richards, and M. Ferris (2019). The gender gap at the top. *Working Mother Research Institute*.

Friebel, G., M. Lalanne, B. Richter, P. Schwardmann, and P. Seabright (2021). Gender differences in social interactions. *Journal of Economic Behavior Organization 186*, 33–45.

Goldin, C. and L. Katz (2016). A Most Egalitarian Profession: Pharmacy and the Evolution of a Family Friendly Occupation. *Journal of Labor Economics 34*(3), 705–745.

Gorshkov, A., A. Fischer, T. Sandoy, and J. Walldorf (2021). Peers and careers: Labor market effects of alumni networks. *Working Paper*.

Goulas, S., R. Megalokonomou, and Y. Zhang (2018). Does the Girl Next Door Affect Your Academic Outcomes and Career Choices? *IZA Discussion Paper* (11910).

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology 78*(6), 1360–1380.

Granovetter, M. S. (1995). *Getting a job: A study of contacts and careers.* 2nd Ed. Chicago: University of Chicago Press.

Guryan, J., K. Kroft, and M. Notowidigdo (2009). Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments. *American Economic Journal: Applied Economics 1*(4), 34–68.

Hacamo, I. and K. Kleiner (2016). Friends with (Wage) Benefits: Random Assignment of MBA Peers and Reallocation to the Financial Industry. *Working Paper*.

Hacamo, I. and K. Kleiner (2017). Competing for Talent: Firms, Managers and Social Networks. *Working Paper*.

Hacamo, I. and K. Kleiner (2020). Confidence spillovers: Evidence from entrepreneurship. *SSRN Working Paper*.

Hindlian, A., S. Lawson, S. Banerjee, H. Shan, D. Mirabal, and E. Campbell-Mohn (2018). Closing the gender gaps: Advancing women in corporate america. Global markets institute, Goldman Sachs.

Hirsch, B. and P. Lentge (2021). Non-base compensation and the gender pay gap. *IZA Working Paper: DP No. 14551*.

Hotz, V. J., P. Johansson, and A. Karimi (2018). Parenthood, family friendly workplaces, and the gender gaps in early work careers. *NBER Working Paper 24173*.

Hsieh, C.-T., E. Hurst, P. Klenow, and C. Jones (2016). The Allocation of Talent and U.S. Economic Growth. *Working Paper*.

Hwang, B.-H. and S. Kim (2009). It pays to have friends. *Journal of Financial Economics 93*(1), 138–158.

Jochmans, K. (2020). Testing random assignment to peer groups. *Cambridge Working Papers in Economics CWPE2024*.

Kalsi, R. and R. Samuels (2019). Why business school is a great time to network. *Harvard Business Review*.

Kirkpatick, S. A. and E. A. Locke (1991). Leadership: do traits matter? *Academy of Management Perspectives 5*(2).

Kleven, H., C. Landais, and J. E. Sogaard (2019). Children and Gender Inequality: Evidence from Denmark. *American Economic Journal: Applied Economics*.

Kremer, M. and D. Levy (2008a). Identification of Endogenous Social Effects: The Reflection Problem. *Journal of Economic Perspectives 22*(3), 189–206.

Kremer, M. and D. Levy (2008b, September). Peer effects and alcohol use among college students. *Journal of Economic Perspectives 22*(3), 189–206.

Lalanne, M. and P. Seabright (2016). The old boy network: The impact of professional networks on remuneration in top executive jobs. *SAFE Working Paper* (123).

Lavy, V. and A. Schlosser (2011). Mechanisms and impacts of gender peer effects at school. *American Economic Journal: Applied Economics 3*(2), 1–33.

Lean In and McKinsey & Company (2015). Women in the workplace. Report 1.

Lean In and McKinsey & Company (2019). Women in the workplace. Report 5.

Lean In and McKinsey & Company (2020). Women in the workplace. Report 6.

Lerner, J. and U. Malmendier (2013). With a Little Help from My (Random) Friends: Success and Failure in Post-Business School Entrepreneurship. *Review of Financial Studies 26*(10), 2411–2452.

Manski, C. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*.

Mas, A. and A. Pallais (2017). Valuing alternative work arrangements. *American Economic Review 107*(12), 3722–59.

Mengel, F. (2020). Gender differences in networking. *The Economic Journal 130*, 1842–1873.

Mishra, S. (2018, Aug). Women in the c-suite: The next frontier in gender diversity.

Moffitt, R. A. (2001). Policy interventions, low level equilibria, and social interactions. *Social Dynamics*, 45–82.

Montgomery, J. D. (1991). Social networks and labor-market outcomes: Toward an economic analysis. *The American Economic Review 81*(5), 1408–1418.

Niederle, M. and L. Vesterlund (2007). Do Women Shy Away From Competition? Do Men Compete Too Much?*. *The Quarterly Journal of Economics 122*(3), 1067–1101.

Olivetti, C. and B. Petrongolo (2016). The evolution of gender gaps in industrialized countries. *Annual Review of Economics 8*(1), 405–434.

Osman, M. (2021, Jul). Mind-blowing linkedin statistics and facts (2021).

Patricia, C. and P. Jessica (2019). When time binds: Substitutes for household production, returns to working long hours, and the skilled gender wage gap. *Journal of Labor Economics 37*(2), 351–398.

Rasul, I. and D. Rogger (2018). Management of bureaucrats and public service delivery: Evidence from the nigerian civil service. *Economic Journal 128*(608), 413–446.

Rosenthal, P. (1995). Gender differences in managers attributions for successful work performance. *Women in Management Review 10*(6), 26–31.

Rosenthal, P., D. Guest, and R. Peccei (1996). Gender differences in managers' causal explanations for their work performance: A study in two organizations. *Academy of Management Perspectives 5*(2).

Sacerdote, B. (2001, 05). Peer Effects with Random Assignment: Results for Dartmouth Roommates*. *The Quarterly Journal of Economics 116*(2), 681–704.

Sacerdote, B. (2011). Peer effects in education: How might they work, how big are they and how much do we know thus far? Volume 3, Chapter 04, pp. 249–277. Elsevier.

Saloner, G. (1985). Old boy networks as screening mechanisms. *Journal of Labor Economics 3*(3), 255–267.

Sandberg, S. and N. Scovell (2013). *Lean In: Women, Work, and the Will to Lead*. Alfred A. Knopf.

Schmutte, I. M. (2015). Job referral networks and the determination of earnings in local labor markets. *Journal of Labor Economics 33*(1), 1–32.

Schneeweis, N. and M. Zweimüller (2009). Girls, girls, girls: gender composition and female school choice. NRN Working Paper, NRN: The Austrian Center for Labor Economics and the Analysis of the Welfare State 0905, Linz.

Shue, K. (2013). Executive Networks and Firm Policies: Evidence from the Random Assignment of MBA Peers. *The Review of Financial Studies 26*(6), 1401–1442.

Sojourner, A. (2013). Identification of peer effects with missing peer data: Evidence from project star*. *The Economic Journal 123*(569), 574–605.

Stinebrickner, R. and T. R. Stinebrickner (2006). What can be learned about peer effects using college roommates? evidence from new survey data and students from disadvantaged backgrounds. *Journal of Public Economics 90*(8), 1435 – 1454.

Thomas, M. (2021). Effects of peer groups on the gender-wage gap and life after the mba: Evidence from the random assignment of mba peers.

Wiswall, M. and B. Zafar (2014, 12). Determinants of College Major Choice: Identification using an Information Experiment. *The Review of Economic Studies 82*(2), 791–824.

Yang, Y., N. Chawla, and B. Uzzi (2019). A network's gender composition and communication pattern predict women's leadership success. *116*(6), 2033–2038.

Zeltzer, D. (2020, April). Gender homophily in referral networks: Consequences for the medicare physician earnings gap. *American Economic Journal: Applied Economics 12*(2), 169–97.

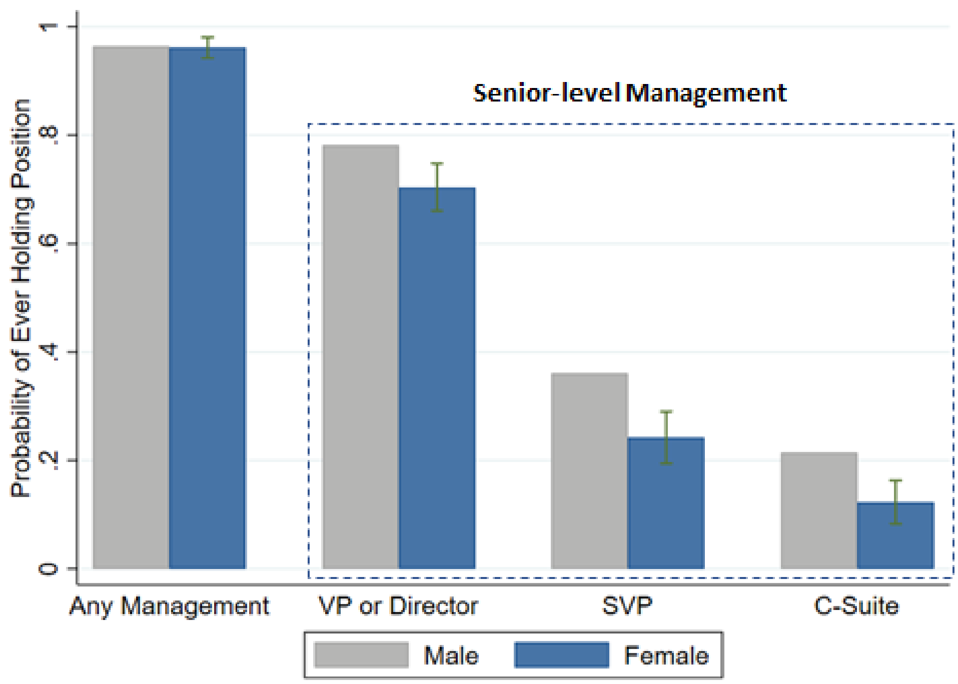
Zimmerman, D. J. (2003, February). Peer Effects in Academic Outcomes: Evidence from a Natural Experiment. *The Review of Economics and Statistics 85*(1), 9–23.

Zimmerman, S. D. (2019, January). Elite colleges and upward mobility to top jobs and top incomes. *American Economic Review 109*(1), 1–47.

Figures and Tables

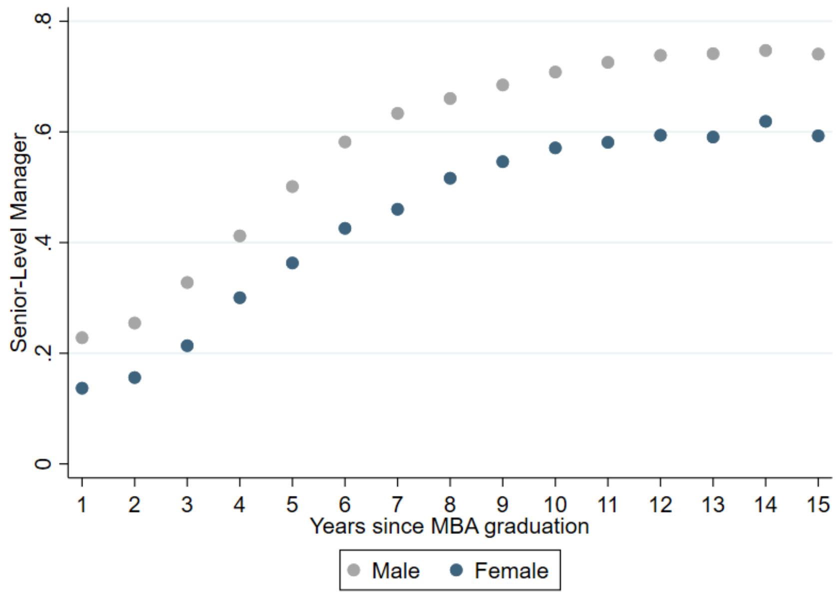
Figures

Figure 1: Representation in the Corporate Pipeline Among MBA Graduates in the First 15 Years Post-Graduation by Gender



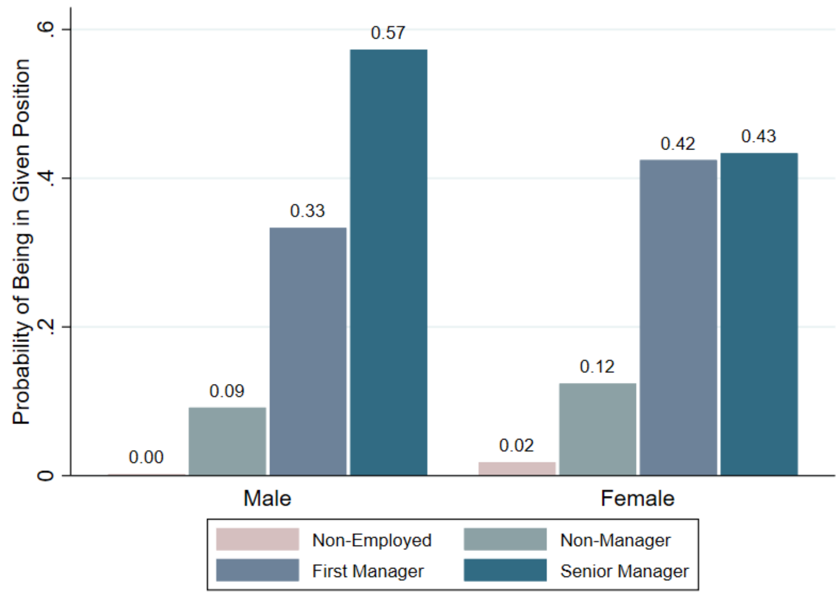
Notes: We plot the percentage of male and female graduates who ever held any managerial positions, a VP or Director position, SVP positions, and C-level Executive position within fifteen years since graduation. We display the 95% confidence intervals from the t-test of gender equality. Sample includes students of the graduating classes 2000-2018, excluding 2009.

Figure 2: Probability of Holding a Senior-Level Management Position by Gender



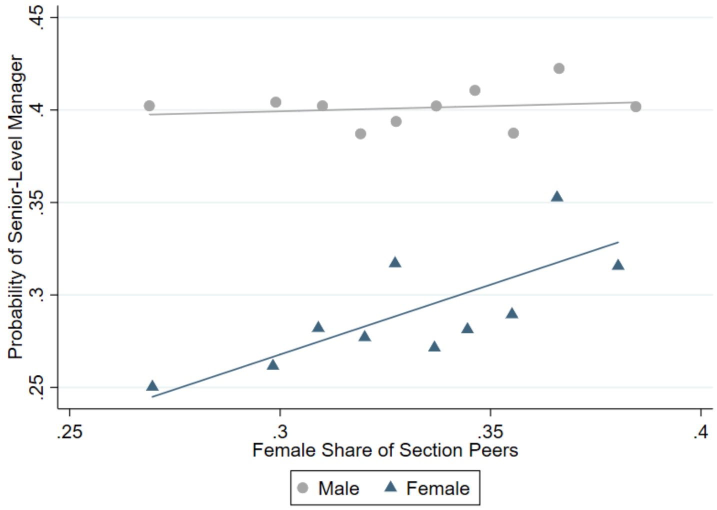
Notes: We plot the percentage of male and female graduates who are holding a senior managerial position over time since graduation. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure 3: Five-Year Transition Probabilities for First-Level Managers by Gender



Notes: We plot the five-year transition probabilities from first-level managerial positions to non-employment, non-managerial positions, first-level managerial positions, and senior-level managerial positions by gender. Sample includes first-level managers from graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

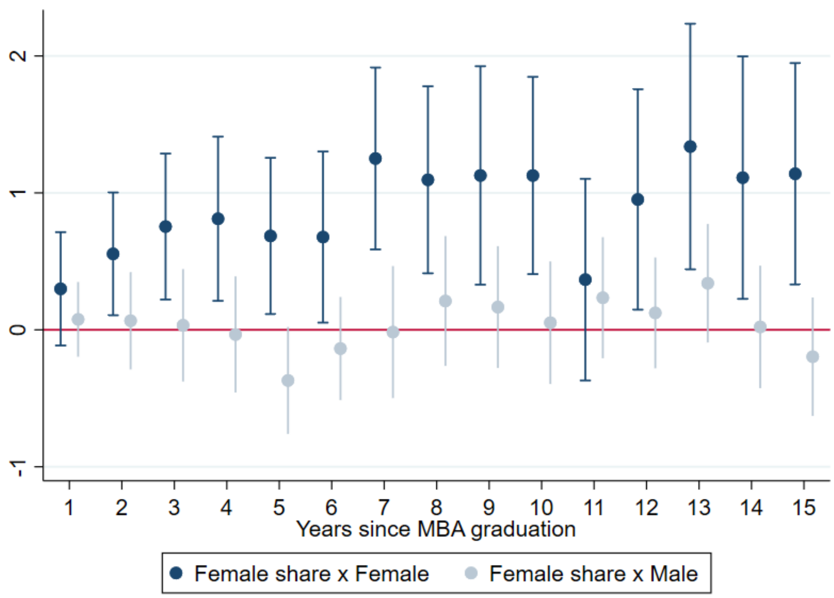
Figure 4: Probability of Senior-Level Manager



Notes: We plot the binned scatterplot of the relationship between female peers and the probability of becoming a senior manager. Both the outcome and female share have been residualized by the full list of controls in our main specification (1). Each dot represents the average likelihood of holding a senior management position within 10-percentile bins of female share. Estimates are separately run for men and women and include class fixed effects, year fixed effects, class-by-year fixed effects, an indicator for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, indicators for having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. Finally, it includes a series of section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign.Sample includes students of graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

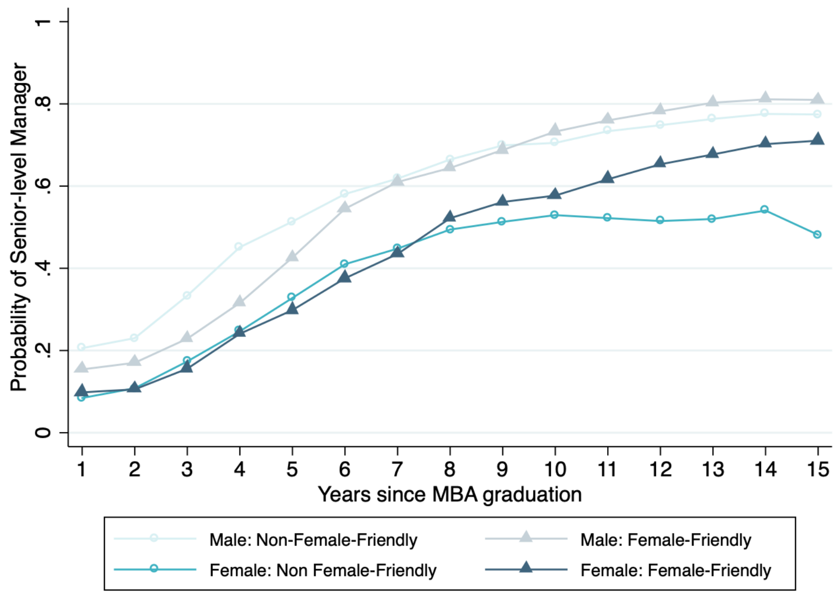
Figure 5: Effect of Female Peers on Senior-Level Management Positions

Figure 6: Effect of Female Peers on Holding Senior-Level Management Positions



Notes: We plot the coefficients for men and women and their 95% confidence intervals from estimating equation (1) separately for each year since graduation. Estimates include class fixed effect, an indicator for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with female dummy. Finally, it includes a series of section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure 7: Probability of Holding a Senior-Level Management Position by Gender and Female-Friendly Firms



Notes: We plot the percentage of male and female graduates who are holding a senior managerial position over time since graduation. We compare this percentage in female-friendly versus non-female-friendly firms. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Tables

Table 1: Randomization Test (Guryan et al., 2009)

	2000-2018		2011-2018	
	(1)	(2)	(3)	(4)
	No Controls	With Controls	No Controls	With Controls
Section Female Share	0.00172	0.00158	0.0336	0.0339
	(0.0155)	(0.0155)	(0.0289)	(0.0290)
Class Female Share	-278.0***	-278.0***	-258.5***	-258.5***
	(2.750)	(2.752)	(3.301)	(3.303)
R^2	.9868657	.986868	.9892842	.9892892
N	5087	5087	2090	2090
Class FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (A1) pooling together all years since graduation (Guryan et al., 2009). Estimations in columns (2) and (4) also include indicators for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Randomization Test (Caeyers and Fafchamps, 2021)

	2000-2018		2011-2018	
	(1) No Controls	(2) With Controls	(3) No Controls	(4) With Controls
Female share	-0.866	-0.931	-0.574	-0.587
	(0.635)	(0.655)	(0.917)	(0.875)
R^2	0.0188	0.00756	0.0145	0.00359
N	5087	4367	2090	1989
Class FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (A2) pooling together all years since graduation (Caeyers and Fafchamps, 2021). Estimations in columns (2) and (4) also include indicators for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect of Female Peers on Senior Management: Pooled Sample

	(1) Senior-Level Manager
Female share × Male	0.0315
	(0.115)
Female share × Female	0.822***
	(0.204)
p-value Male vs. Female	0.000
Female Mean	0.391
Male Mean	0.534
R^2	0.173
N	51440
Class x Year x Female FE	Yes
Stratification Controls	Yes
Pre-MBA Characteristics Controls	Yes
Section-level Controls	Yes

Notes: We present the coefficients for men and women from estimating equation (1) pooling together all years since graduation. Estimates include class fixed effects, year fixed effects class-by-year fixed effects, an indicator for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, indicators for having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. Finally, it includes a series of section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Non-Linear Effect of Female Peers on Senior Management: Pooled Sample

	(1) Senior-Level Manager
Female Share Below Median	0.939***
	(0.284)
Female Share Above Median	0.603
	(0.375)
p-value Below Median vs. Above Median	0.514
Female Mean	0.391
Male Mean	0.534
N	51440
Class x Year x Female FE	Yes

Notes: We present the coefficients for sections with female share below and above the median (across all classes) from estimating equation (A3) pooling together all years since graduation. Estimates include class fixed effects, year fixed effects class-by-year fixed effects, indicators for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. We also control for the following section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of Female Peers on Probability of Senior Management in Female-Friendly Firms

	Senior Manager		
	(1) Female-Friendly Firms	(2) Non Female-Friendly Firms	(3) Female-Friendly Firms
Female share × Female	1.243***	-0.468	0.857
	(0.394)	(0.402)	(0.915)
Female Mean	0.161	0.118	0.532
Male Mean	0.238	0.186	0.542
R^2	0.167	0.242	0.123
N	28505	28505	28505
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Estimates include class fixed effects, year fixed effects class-by-year fixed effects, indicators for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. We also control for the following section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Referral Effect: Probability of Entering the Same Firm

	(1)
Same Section	0.000071
	(0.000264)
Same Section × Both Males	-0.000092
	(0.000333)
Same Section × Both Females	0.001260**
	(0.000640)
p-value Both Male vs. Both Female	.034460
Female Mean	.006549
Male Mean	.006420
R^2	.040879
N	11,991,054
Class x Year FE	Yes
Firm FE	Yes

Notes: We present the coefficients for men and women from estimating equation (2) pooling together all years since graduation. Estimates include class fixed effects, year fixed effects, class-by-year fixed effects, and firm fixed effects. Dataset created by matching each MBA graduate (from graduating classes 2000-2018, excluding 2009) with all possible classmates of the same graduating year. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For Online Publication

Appendix

A Data Appendix

A.1 Description of Business School Administrative Data

The administrative data set is comprised of six sources of individual-level information between 2011 and 2018; (1) demographics which include gender, ethnicity, citizenship, and age; (2) pre-MBA educational background, which includes, all prior degrees, GMAT scores, and previous GPA; (3) employment information which includes pre- and post-career outcomes and associated industry, base salary and bonus compensation; (4) coursework taken and grades; and (5) section assignment. This dataset was created via merging of several administrative datasets from different departments such as the registrar and career services.

A.2 Description of LinkedIn Data

LinkedIn is a social media platform used primarily for professional networking. It allows job seekers to post their CVs and employers to post jobs. The platform is widely used with over 740 million members worldwide in 2021. In the United States, there are over 170 million users (Osman, 2021). It is popular among professionals with 50% of the users holding a college degree (Osman, 2021).

Users create online public profiles that contain CV information. This contains information on all previous work experience, including job title, employer, location, job descriptions, start and end dates. Individuals can also post education and training, skills, and a personal photo. In addition, individuals can connect with other users on the platform in an online social network. In our analysis, we use the work and education background information.

Moreover, the platform also has public company pages. These pages contain information on the company website, industry, company size, headquarters location, type (public, private, nonprofit, government), founding year, and specialties. On individual profiles, the employer is often linked to one of these company pages. We use these pages to construct a unique employer identifier as different firm aliases will often be linked to the same company profile.

We collected this data in May and June of 2019. As a result, the CV information is current up to 2019. In our main analysis, we restrict to individuals whose locality is the

United States. The data is cleaned by parsing the information on the CV and reshaping the data such that a quarterly panel is created based on the start and end dates of employment. We expand the data to include observations for when someone is in nonemployment, i.e. periods where there is a gap on the CV between the start and end dates of two consecutive positions. We then collapse the dataset to the yearly level. For each year, individuals are assigned to the position in which they have spent the most time during that year. If there are ties, the position with the longer tenure takes precedence.

A.3 Description of Alumni Directory Data

The alumni directory provides alumni with the opportunity to contact and network with fellow alums. It contains full name, current location, all degrees conferred at the university, MBA section, undergraduate institution, student activities such as club affiliations, and current employer information, including employer name, industry, job title and start dates. In some cases, alumni also include links to their social media platforms such as personal websites, LinkedIn or WeChat ID. The directory also facilitates networking by providing a way for alumni to email each other through the platform. Information related to university degrees and sections is pre-filled by the school. Alumni can update their location and employment information at any time. This data was accessed and collected in May and June of 2019 for our analysis.

A.4 Description of Glassdoor Data

Glassdoor is an online platform where employees can anonymously submit salaries and rate their companies. We obtained 10.5 self-reported compensation records for 630,422 firms from 2006 to 2017. Each observation is a salary report with information on the employer, employment status (e.g., regular, part-time, contract), job title, gender of the reviewer, compensation and its components. For compensation, there is the base pay amount and whether the base pay period is denoted annually or monthly. Non-base compensation is also available for cash bonus, stock bonus, profit sharing, sales and commission, and tips. In our analysis, we use only data from regular employees who reported their annual base pay. Using the same procedure described in Section 3.5, we assign management level using the job titles available in this dataset. We classify all positions into non-management, first-level management, and senior-level management. We then aggregated this data to the firm, gender, and management level by taking the mean base and total (i.e., sum of base plus non-base components) compensation of that corresponding cell. Note that we do not have gender information for 36% of the sample. Once aggregated, we construct the following measures: share of reviews by women (which proxies for female share of employees), share of reviews by senior managers that are women, average (base/total) compensation at the firm level by gender, and average (base/total) compensation for senior managers by gender. Using these measures, we also construct additional outcomes such as the gender gap in compensation. We then match these firm-level statistics to the firms in LinkedIn using the firm name.

We also use this dataset to impute compensation for individuals in the LinkedIn dataset. To do so, we match individuals to the average compensation of their firm based on their gender and management level.

A.5 Description of Female-Friendly Firm Data

A.5.1 InHerSight

InHerSight is an online platform that allows women to rate their companies anonymously on a scale of 1 to 5 on 18 metrics in six categories that are designed to capture how well companies support women. These include:

1. Gender Equal Opportunities
    - Equal Opportunities for Women and Men (Promotions, leadership roles, salary increases, incentive programs)
    - Management Opportunities (Your chances of becoming a manager of teams and talent)
    - Women in Leadership (Women on the executive team, in senior leadership)
2. Work Schedule Flexibility
    - Paid Time Off (Sick days, vacation days, and personal days)
    - Flexible Work Hours (Ability to set your schedule as long as you get your work done)
    - Ability to Telecommute (Flexibility to work remotely)
3. Professional Enrichment

- Wellness Initiatives (On-site gym, gym discounts, walking desks, healthy food options)
- Learning Opportunities (On and off-site skills training, speaker series, conferences)
- Sponsorship or Mentorship Program (Official mentorship program, women-focused initiatives or affiliate groups)
- Do you feel your growth and success are (or were) priorities for your manager(s) at this company?
- Do you feel you receive (or received) the necessary feedback to succeed at your job and achieve your goals at this organization?

4. Fair Compensation

   - Salary Satisfaction (Salary, merit increases, cost of living adjustments, overall comp)
   - When reflecting on your salary or pay when you were first hired at this company, do you feel you were paid fairly?

5. Family Friendliness

   - Maternity and Adoptive Leave (Paid parental leave policies, job security, support for returning moms)
   - Family Growth Support (Access to dedicated lactation rooms, child care, expense reimbursement)
   - Does this company support employees caring for other members of their family or extended family other than children?

6. Workplace Culture

   - The People You Work With (Respectful, professional, unbiased, all those good things)
   - Social Activities and Environment (Happy hours, game room, company outings, and other perks)
   - Support for Diversity (People and programs that prioritize diversity, inclusion, equity and belonging)

- Sense of Belonging (Comfortable bringing your whole self to work, you feel included and welcome)
- Employer Responsiveness (Effective channels for elevating issues and concerns)

In addition to the measures listed, InHerSight also creates an overall firm five-star rating based on these metrics. The website also provides the number of reviews for each firm. In our analysis, we will use the star rating and the individual components. We also create standardized indices for each of the six categories by first standardizing each of the components and taking the average. We accessed the data on the website in May 2021 for all available companies. We then matched the companies based on the name to the firms in LinkedIn. We utilize firm location to identify companies with multiple matches.

A.5.2 FairyGodBoss

FairyGodBoss is an online crowdsourcing platform that aggregates online reviews and company data for women. The website collects information on the number of paid or unpaid weeks of maternity and paternity leave. It also collects employee reviews. For each firm, there is an overall company rating out of five stars. We collected the available data on parental leave from the web and then manually searched for the LinkedIn companies on this website to collect the company ratings.

A.5.3 50/50 Women on Boards

50/50 Women on Boards is a nonprofit, advocacy group that is committed to advancing women to corporate boards. The group has maintained a web directory "50/50 Women on Boards Gender Diversity Directory and Index" that tracks the number of women among the corporate board members on the Russell 3000 Index. We downloaded and accessed this directory in May 2021.

A.5.4 Validation of the Female-Friendly Measure

To validate our primary measure of female-friendliness, we explore the correlation among these multiple metrics. Appendix Figure A19 shows the correlation between the InHerSight overall star rating, the InHerSight six standardized indices, the FairyGodBoss overall rating, the FairyGodBoss number of weeks of paid maternity leave, and the percentage of female board members from 50/50 Women On Boards. As expected, the InHerSight measures are highly correlated to each other. Interestingly, the FairyGodBoss overall rating has the highest correlation with the InHerSight overall rating. Similarly, the FairyGodBoss number of weeks of paid maternity leave has the highest correlation with the InHerSight index related to family-friendliness, which includes rating on maternity and paternity leave. Finally, the percentage of female board members from 50/50 Women On Boards has the highest correlation with the InHerSight index related to gender equal opportunities, which includes metrics such as female representation in leadership and management opportunities.

A.6 Description of Survey Data

The survey was distributed online by the university alumni relations office via email in February and March 2021 to a 10% sample of MBA graduates residing in the United States at the time of the survey. The sample includes two-year full-time MBAs, part-time MBAs, and executive MBAs. The response rate is 30%.[81] Total number of responses was 328. Of which, 49% are two-year full-time MBA graduates.

B Classification of Job Functions

We utilize the job titles available on the LinkedIn profiles to classify job positions into functions. To do so, we match job titles to the open-source dataset, Thesaurus of Job Titles (Carty, 2017). This dataset links job titles and their synonyms to standardized SOC codes as well as detailed function categories. Using this dataset, we classify 93% (17,651 out of 18,982 job titles) of the job positions in our dataset into broad function categories. These are Accounting, Administrative, Consulting, Customer Service, Finance, General Management, Human Resources, IT, Legal, Marketing, Operations/Logistics, PR/Communications, Product Management, Research, Sales, Strategic Planning, and Other. Recent studies suggested that one barrier to female advancement into executive positions is the lack of profit and loss (P&L) responsibilities, or having full control over the profitability for a department or an entire organization (Lean In and McKinsey & Company, 2015). We identify P&L positions based on whether the job function is in General Management, Operations/Logistics, Product Management, Sales or Strategic Planning.

[81] This is similar to response rate in the literature for similar populations. For example, Bertrand et al. (2010) had a response rate of 31% for University of Chicago MBA graduates.

C Definition of Managers

Our dataset allows us to identify management positions based on keywords in job titles listed on the MBA graduates' online profiles. We run a textual analysis on job titles to categorized managers in the following positions following the definitions suggested in the LeanIn.org and McKinsey & Company (2020) report:

- **C-Level Executives**: Executives such as CEO, CFO, COO, responsible for company operations and profitability. Keywords: "Chief X Officer", "President."

- **Senior Vice Presidents**: Senior leaders with significant business unit or functional oversight. Keywords: "SVP","General Manager","Managing Director."

- **Vice President and Director**: Leaders responsible for activities/initiatives within a sub-business unit, or who report directly to SVP. Keywords: "VP","Director","Regional Managers."

- **Managers**: Leaders responsible for teams and discrete functions or operating units. Keywords:"Manager", "Senior Product Manager."

C.1 Summary Statistics

In this section, we provide summary statistics for our sample. Appendix Table A1 presents the means and standard deviations for demographics and pre-MBA background information for the full sample and by gender.[82] In Panel A, we report the demographics information.[83] In our full sample, 36% of students are female. For the classes of 2011-2018, the average age of students in the year of graduation is 30. Male students are on average 0.85 years older and are 8 percentage points less likely to be U.S. citizens compared to female students. 65% of students are white. Female students are more likely to be of a minority race; they are 3 percentage points more likely to be black or Hispanic. Compared to female students, males have slightly higher GMAT total score, consistent with previous findings in the literature (Bertrand et al., 2010).

[82] All statistics in this table are measured at the person-level. We also report in the last column the gender difference in means and the p-values from the two-sample t-test.

[83] Except for the statistics on percentage of female students, all other demographics data are available only in the administrative data for the cohorts graduating between 2011 and 2018.

In Panel B, we report the descriptive statistics for pre-MBA background characteristics.[84] MBA students have around 5 years of work experience and 39% have held a management position prior to the MBA. A smaller percentage of students (13%) have held a senior management position. There is no gender difference in management experience prior to the MBA, but there is a gender difference in compensation. Average imputed total compensation in the three years prior to graduate school is $123,350. There is a gender gap of $25,890, or 21%. 64% of male students compared with 61% of female students have worked in a male-dominated industry (finance, tech or consulting). Finally, we find that women are more likely to have graduated from a top 20 undergraduate program.[85]

Appendix Table A2 presents the descriptive statistics for the set of academic and career outcome variables in our analysis. Panel A shows outcomes that are available in the administrative data, measured at the person level. During the MBA, male students have a higher overall GPA by 0.06 points and take 29% more finance classes as a proportion of all classes taken during the MBA. Previous work has found that the gender difference in finance courses can help explain the gender wage gap for MBA graduates (Bertrand et al., 2010).

In Panel B, we present the statistics for career outcomes measured at the person-year level. 75% of graduates are in a management role while 43% are in a senior management role. Although women are equally likely to be in a management position, they are 14 percentage points, or 29.8% less likely to hold a senior management position. Men are 1 percentage point more likely to be employed than women and women have a higher number of cumulative months of nonemployment. The imputed base annual compensation averages $133,000, while total compensation is $223,310. This is a 45% increase compared to $123,350 in total compensation prior to the MBA. Gender difference in compensation also increases substantially. While women earn on average 17% less than men in terms of base compensation, this gap increases to 33% for total compensation. This suggests that a substantial portion of the gender difference in compensation comes from the gender difference in non-base compensa-

[84] These measures come from the main LinkedIn dataset for our sample of full-time MBAs who graduated between 2000 and 2018, excluding class of 2009. Except for pre-MBA years of experience, the statistics are measured two to five years prior to MBA graduation, i.e. the three years prior to entry into the MBA program. For pre-MBA experience, we use the total number of years with work experience listed on the online profile for the ten years prior to the MBA.

[85] Top 20 undergraduate programs are defined by the top 20 universities ranked by U.S. News in 2020. These universities are the Ivy League universities as well as MIT, Stanford, University of Chicago, Caltech, Johns Hopkin, Northwestern, Duke, Vanderbilt, Rice, Washington University in St. Louis, University of Notre Dame, and UCLA.

tion.[86,87] In terms of industry choice, 59% of students work in a male-dominated industry. This includes finance, technology, and consulting. We define male-dominated industries as those where women are relatively more underrepresented. In Appendix Figure A3, we present the female share of MBA graduates working in each of the six industry categories in our data. While women make up on average 36% of the MBA graduates, they are disproportionately represented in the female-dominated industries (consumer goods and healthcare) and underrepresented in the three male-dominated industries (consulting, tech, and finance). Consistent with this pattern, we observe in Appendix Table A2 that women are 15 percentage points less likely to enter male-dominated industries. Finally, we find that women are more likely to work in larger firms. There is no gender difference in the female-friendliness of the firm. Similar to what we documented for pre-MBA background characteristics, there are no gender differences in having Profit and Loss (P&L) responsibilities.[88]

D Summary Statistics: Compensation

In this section, we compare the average values of the imputed total compensation with self-reported values from the survey sample and the mean values for the sample of University of Chicago Booth MBAs who graduated between 1990 and 2006 in Bertrand et al. (2010). Figure A2 suggests that the imputed compensation is likely an underestimate of the true compensation especially in the later years of the career trajectory. However, the gender gap in compensation in percentage terms is similar in magnitude across the different sources. In Bertrand et al. (2010), there is a gender difference of 34% and in the survey results, there is a gender difference of 25%.[89] This compares well with the 31% gender gap we document.

[86]Non-base compensation includes cash or stock bonus, profits sharing, sales and commission, and tips.

[87]Note that the compensation reported is an imputation and does not reflect the actual compensation received by the MBA graduates. In Appendix Section D we compare the average values of the imputed total compensation with self-reported values from the survey sample and the mean values for the sample of University of Chicago Booth MBAs who graduated between 1990 and 2006 in Bertrand et al. (2010).

[88]Profit and Loss (P&L) responsibility consists in monitoring the net income after expenses for a department or an entire organization, with direct influence on how company resources are allocated. These roles have been shown to be essential for promotions into top executive positions.

[89]Online Appendix Table A3 of Bertrand et al. (2010) reports an average post-MBA compensation of $228,236 for all students, $249,938 for male students and $164,417 for female students. The average post-MBA compensation in the survey is $282,897 for all students, $306,739 for male students and $ 231,392 for female students.

E Match Statistics

In Appendix Table A18, we summarize the match rate across the different datasets in our sample. Panel A describes the main analysis sample of individuals who graduated between 2000 and 2018, excluding 2009. Of the universe of two-year full-time MBAs, we matched 77% to their LinkedIn profiles.[90] We conduct the matching via two methods. First, the administrative records of the business school were matched to public LinkedIn profiles for graduates from 2011 to 2018. This is done securely by university personnel. Second, because administrative records are not available for earlier cohorts, we use alumni directory records to identify MBA graduates of 2000 to 2010. The matching is done manually using web searches based on information available in the alumni directory: first name, last name, and year of graduation.[91] In Appendix Section F, we provide additional details on the alumni directory sample and how the match procedure was conducted. We exclude the class of 2009 from our analysis because a large majority of this class has private or missing alumni profiles.[92] Importantly, the directory also lists the MBA section of the graduate. We use this information to assign to each graduate the proportion of female students in their section (the key treatment variable for our analysis), calculated using administrative data. We have in total 6,556 matched profiles and 71,546 observations for the first fifteen years post graduation. Restricting our sample to individuals that are based in the United States further reduces the number of individuals to 5,097 and 56,073 total observations. This restriction represents 60% of all graduates and 78% of the full Linkedin dataset.

In Panel B, we present the match rate across the different firm datasets for our sample. There are 6,688 unique firms in the final US-based LinkedIn sample for the first fifteen years post MBA graduation. 67% of these firms have a LinkedIn company profile, which has information on industry and firm size. 44% of the firms are successfully matched to the Glassdoor compensation data. Information on female-friendly firms are available for a smaller number of firms with 21% are matched to InHerSight, 7% to FairyGodBoss and 9% to 50/50 Women on Boards. It is important to note that larger firms are more likely

[90] In Appendix Table A44, we report the matching rate by class and gender. The match rate differs across classes, ranging from 65% to 90%. The match rate across genders also differs; 80% of males and 72% of females are matched.

[91] We used undergraduate institution and current employer to confirm any potential matches.

[92] In 2009, only 94 out of 526 graduates had available directory records. Note that 2009 was the year where the employment rate fell for many business school programs. At the top ten business schools, MBA employment rates at graduation dropped an average of 21% from 2007 (Byrne, 2020).

to have information across all of these datasets. As a result, the match rate for unit-year observations is much higher. For example, even though only 21% of firms are matched to InHerSight, this information is available for 52% of the sample.

In Panel C, we report the number of observations for the administrative data and the number of matched observations to the LinkedIn data. 81% of the students represented in the administrative records have been matched to the LinkedIn dataset, and 61% are based in the U.S.[93] Finally, in Panel D, we report the number of observations in the survey data.

F Matching between Alumni Directory and LinkedIn Profile

Starting from our alumni directory for classes 2000 to 2010, we collected publicly available LinkedIn data for this sample. We exclude the class of 2009 because a large majority of this class had private or missing alumni profiles. We matched alumni to their online profiles based on the following variables:

- Full name
- Business school name listed on the social media profile
- Year of graduation
- Recent employment
- Undergraduate institution

We require names, business school and class year to match perfectly to be considered a match. For women, we require only the first names to match and we conduct an online verification for those that may have changed their last names due to marriage (e.g., a wedding registry webpage). We utilize the name of recent employer and undergraduate institution when available to verify matches.

One potential concern of using the alumni directory records to define the sample universe for the older cohorts is the possible selection of graduates who choose to make their profiles

[93] Note that the matching rate is not 100% because the school administration is currently still in the process of matching the LinkedIn profiles.

public. For example, individuals who are more successful or have stronger connections to their MBA network may be more likely to have public directory records. However, Appendix Table A45 shows that, compared to the total number of graduates from official administrative statistics, nearly all graduates, 96%, are represented in the alumni directory.[94] The high coverage rate of the alumni directory suggests that selection is likely limited in this setting. Moreover, because the alumni directory provides the section number of each graduate, individuals are assigned to the true proportion of female peers in their section despite not having a complete census of graduates in the alumni directory records.

F.1 Gender Differences Among Senior Managers

In addition to substantial gender differences in the career progression of MBA graduates, we also document gender differences among those who are promoted into senior-level management. These differences provide insights into how female peers may help women advance into senior management.

Appendix Table A51 reports the summary statistics by gender for the sample of senior managers. We show that female managers are slightly more likely to work in female-friendly firms, 73% compared to 70% of male managers. This may be reflective of the emphasis in female-friendly firms in creating a supportive environment for nurturing female talent by providing parental support and leadership development.[95] Women are also 10 percentage points or 12% less likely to be a senior-level manager in a male-dominated industry. They are more likely to be managers in slightly larger firms and firms with more female employees and female management representation, as proxied by female share of Glassdoor employee reviews. They are also employed in firms with a lower gender gap in total compensation at the firm level and for senior managers. Similar to the results on female-friendly ratings, this suggests that career advancement of women may depend on having access to firms with more gender-equal opportunities or career support. Contrary to other studies of high-skilled workers (Mishra, 2018), female graduates of this university are not less likely to be in an P&L role, defined as job functions in General Management, Operations/Logistics, Product Management, Sales or Strategic Planning. Having experience in one of these roles is an important qualification for advancing into top executive management positions (Byham and Fraser, 2021). However, because the job functions in our dataset are inferred using job titles

[94] Coverage rate by class year is provided in Appendix Table A46.

[95] See, for example, `https://www.inhersight.com/about`.

rather than detailed descriptions of job responsibilities, general management may include positions without P&L responsibilities. To complement these results, we turn to our survey data which directly asks for P&L responsibilities, as well as reports and compensation.

In Appendix Table A52, we show, using the survey results, that conditional on being a senior-level manager, women have fewer responsibilities than their male counterparts. On average, male managers work 2.98 additional hours per week and oversee 164 employees, including direct and indirect reports, while female managers oversee 36 employees. This represents a difference of 129 employees. As in our previous results, we find that female senior managers are more likely to work in larger firms. However, we find that male senior-level managers are 25 percentage points significantly more likely to report having P&L responsibilities in contrast to the results using the LinkedIn data. This difference in P&L responsibilities across genders may be indicative of additional barriers facing women, such as the lack of information and career advice. For example, recent reports and surveys have increasingly shown that women are systematically less aware of the importance of P&L roles (Byham and Fraser, 2021). In their study, Frankel et al. (2019) highlight that women are 69% less likely to receive detailed information about the career paths toward P&L roles.

We also document that female managers are less ambitious than male managers. They are 34 percentage points less likely to report they would like to be a CEO in five years. Interestingly, we find contrasting patterns in negotiation. Despite similar patterns in asking for raises and promotions, male senior managers are significantly more likely to have successfully negotiated for a raise. 100% of male senior managers receive a raise when they ask, compared to 93% of women. On the other hand, we do observe that men are slightly less successful at negotiating for a promotion, compared to 100% of the female senior managers. Because this sample is restricted to senior managers only, the women we observe may be precisely those that negotiated successfully. Together, these results highlight several potential avenues in which a larger network of female peers can help women advance. For example, networks may facilitate transmission of information about female-friendly firms and P&L roles. They may also help raise women's ambitions and provide advice on negotiation.

These results highlight several potential avenues a larger network of female peers can help women advance. For example, networks may facilitate transmission of information about female-friendly firms. They may also help raise women's ambitions and provide advice on negotiation.

F.2 Explaining the Gender Differences in Senior Management

In this section we turn to understanding what explains the gender gap in senior management positions. We show that education background, work experience, industry and firm characteristics cannot fully explain this gender gap. In Table A47, we present coefficient estimates from regressing a dummy for holding a senior management position on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and additional controls using the pooled sample of all individual-year observations. The female coefficient represents the gender gap in the likelihood of holding a senior management position. Column (1) shows that without any additional controls, there is a substantial gender gap of 24% (=0.128/0.543) in senior management despite similar educational backgrounds and levels of human capital among MBA graduates. Adding pre-MBA characteristics that include years of experience, top 20 undergraduate institution, management experience, P&L experience explains only 0.2 percentage points of the gap in Column (2). Including the pre-MBA industry explains 4.6% of the gender difference (Column (3)). In Column (4), we include cumulative months of career break as a control. Career interruptions and breaks associated with parenthood have been linked to the gender gap in compensation and career outcomes of women (Bertrand et al., 2010; Kleven et al., 2019). While we do not have childbirth information, we are able to infer career breaks based on the employment dates listed on the online profiles.[96] Including this control explains a small percentage of the gap. Then in Columns (5) and (6), we include additional post-MBA controls such as experience, firm size, P&L role, as well as industry fixed effects. The gender gap, however, remains significant and sizeable at 17.7% (=0.0959/0.545), suggesting that the common determinants of the gender wage gap, such as industry and work experience, that we can observe in the LinkedIn dataset cannot explain most of the gap.

It should be noted that we do not observe all potential important predictors of the management gap in our LinkedIn dataset, such as academic ability, and some of the observables may be measured with error when inferred from the CV data. For example, individuals may not accurately report their start and end dates at each firm, which may lead to measurement error in the career break variable. Women and men may not necessarily report maternity or paternity leaves if these are employer-sponsored and there is no change in employer. For

[96] Specifically, we identify career breaks if there is at least a 3-month gap between the end and start dates of two consecutive positions.

these reasons, we now present results exploring the gender gap in management using additional characteristics, including firm covariates from Glassdoor and InHerSight, academic outcomes from the linked administrative dataset, and family background from the survey data.

First, in Appendix Table A48, we include additional firm characteristics from Glassdoor and InHerSight. Although the sample size is reduced, we find a consistent pattern with respect to the previous results.

Second, to study how academic outcomes may explain the gender gap in senior management, in Appendix Table A49, we replicate the previous analysis using the smaller sample of graduates in the 2011-2018 cohorts whose academic records were matched to their LinkedIn profiles. We show that in the more recent cohorts, a gender gap also exists in senior management. The table shows the gender gap closes after controlling for academic performance (GPA), GMAT scores and share of finance classes taken. This provides suggestive, albeit imprecise, evidence that academic performance can explain the gender gap in management, consistently with prior results in the literature that show the importance of finance classes and MBA academic achievement in explaining the gender wage gap (Bertrand et al., 2010). However, the MBA graduates in this sample are much younger and as of 2019, when the LinkedIn profile data were collected, have on average only 1 to 8 years of postgraduate work experience. To the extent that the influence of academic outcomes may lessen over time, it may not necessarily fully explain the gender gap we observe in the full sample. Moreover, given that the sample sizes are much smaller, we can not exclude that these results are driven by loss of power.

Third, to supplement this analysis, we also turn to our survey results which allow us to control for a richer set of observable characteristics that are, arguably, better measured. However, this is a much smaller sample and can reflect a selection of MBA graduates. In Appendix Table A50, we show that in the survey sample, female MBAs are 11.4 percentage points less likely to hold senior management positions. This difference cannot be explained by differences in weekly hours worked. Adding in the number of children shrinks the gender gap by 8.7%. Controlling for the pre-school child care responsibilities and employment gap after childbirth explains the remaining gap. These results are in support of previous work in the gender wage gap literature (Bertrand et al., 2010; Blau and Kahn, 2017). For example, Bertrand et al. (2010) showed the compensation gap among MBA graduates can be explained by career interruptions and reduced labor supply associated with motherhood.

A similar pattern also emerges when we use compensation as our dependent variable.[97,98] More detailed explorations of the determinants of the management gap is a subject for future research.

G Empirical Challenges

The literature has highlighted three main issues in the identification of peer effects (e.g., Manski, 1993; Sacerdote, 2011, 2001; Brock and Durlauf, 2001; Moffitt, 2001; de Paula, 2017; Charles et al., 2018; Caeyers and Fafchamps, 2021). First, peers may be endogenous due to self-selection into peer groups and networks (Kremer and Levy, 2008b; Duflo and Saez, 2003). This is referred to as selection bias. In our context, unobserved characteristics, such as extroversion, may positively affect both the size of the network and the likelihood of attaining senior managerial positions. We address this issue by exploiting the exogenous variation in exposure to female peers that comes from the random assignment of MBA students to sections.[99]

Second, peer effect estimations may be affected by the presence of unobserved correlated effects within the pool from which peers are selected. For example, there may be common shocks, such as graduating during a recession year, that affect both peers and the individual (Sacerdote, 2001; Kremer and Levy, 2008a). We tackle this issue by including class fixed effects in our estimation. Common shocks may also emerge at the peer group level within classes (Lerner and Malmendier, 2013). By focusing on a pre-determined characteristic, gender, we are able to isolate peer effects from the potential confounding effect of common shocks.[100] In fact, the random assignment makes it unlikely that common shocks are correlated with this predetermined characteristic (Lerner and Malmendier, 2013).

Third, peer effects estimation can also suffer from the reflection bias. In the commonly-estimated linear-in-means model, the outcome is modeled as a function of peers' average outcomes, individual's background characteristics, and peers' average background characteristics (Sacerdote, 2011).[101] Because individuals in the same peer group affect each other,

[97] See Appendix Table A58.

[98] As in the previous case, given the smaller sample sizes, we can not exclude that these results are driven by loss of power.

[99] For more details on the random assignment of students into sections, see Section 2.

[100] For example, by having the same professors in the core classes, students in the same section may have more similar labor market outcomes. However, the assignment of professors are not correlated with the share of female students in the section due to random assignment.

[101] For example, $Y_i = \alpha + \beta_1 \bar{Y}_{-i} + \gamma X_i + \gamma_2 \bar{X}_{-i} + \epsilon_i$, where $\bar{Y}_{-i}$ is the peers' average outcome, and X

estimates of this model are biased due to a multiplier effect, highlighted by Manski (1993) as the reflection problem. This introduces an endogeneity bias in these outcome-on-outcome linear-in-means models. However, because we are interested in the effect of a predetermined characteristic of the peers, we model the outcome only as a function of an individuals background characteristics and peers average background characteristics. Therefore, our estimates do not suffer from this problem.

H Randomization Test (Guryan et al., 2009)

The randomization test proposed by Guryan et al. (2009) is implemented by estimating the equation:

$$x_{ikc} = \pi_1 + \pi_2 \bar{x}_{-i,k} + \pi_3 \bar{x}_{-i,c} + \delta_c + X_{ikc}\gamma' + u_{ikc} \tag{A1}$$

where x_{ikc} is the gender dummy for individual i in section k and class c. X_{ikc} is the class fixed effect. $\bar{x}_{-i,k}$ is the leave-out mean of female share in the section. $\bar{x}_{-i,c}$ is the leave-out mean of female share in the class. This last term is the bias correction term that addresses the exclusion bias. The rationale behind this test is that, after controlling for the class-level leave-out mean, the section-level leave-out mean should be precisely estimated and not significantly different from zero. That is, random peer assignment can be verified by testing if $\hat{\pi}_2 = 0$.

I Randomization Test (Caeyers and Fafchamps, 2021)

The randomization test proposed by Caeyers and Fafchamps (2021) is implemented by estimating the equation:

$$\tilde{x}_{ikc} = \phi_1 + \phi_2 \bar{x}_{-ikc} + \delta_c + u_{ikc} \tag{A2}$$

where i is the individual, k is the section, c is the class cohort. $\tilde{x}_{ikl}$ is defined as $x_{ikc} - \rho \bar{x}_{-ikc}$ and $\rho = plim_{N\to\infty}[\hat{\beta}_1]$, which captures the asymptotic exclusion bias. As in Guryan et al.

denote background characteristics.

(2009), we would reject the null of random assignment if $\hat{\phi}_2$ is significantly different from zero. In Proposition 2 of Caeyers and Fafchamps (2021), the authors show that for cases with varying group (section) sizes and pool (class) sizes, ρ is given by

$$
\begin{aligned}
plim_{N\to\infty}[\hat{\beta}_1] &= \sum_k \frac{K_k}{M} \frac{s^2_{z_k}}{s^2_z} plim_{N\to\infty}[\hat{\beta}_{1k}] \\
plim_{N\to\infty}[\hat{\beta}_{1k}] &= -1 \frac{(L_k - 1)(K_k - 1)}{(L_k - K_k)L_k + (K_k - 1)} \\
s^2_{z_k} &= \frac{(K_k - 1) + (L_k - K_k)L_k}{L_k(L_k - 1)(K_k - 1)} \\
s^2_z &= \sum_k \frac{K_k}{M} s^2_{z_k} \\
M &= \sum_k K_k
\end{aligned}
$$

where K_k is the size of a given group (section) k and L_k is the pool (class) size. According to Caeyers and Fafchamps (2021), we can test random peer assignment by using OLS standard errors clustered at the pool (class) level. To include covariates, we first partialled out the regressors following the procedure described in Caeyers and Fafchamps (2021).

J Actual and Simulated Distribution of the Share of Female Peers

In this section, we provide additional evidence that the within-class distribution of the share of female peers is as good as random. Specifically, we follow the methodology in Bietenbeck (2020) and we compare the actual within-class distribution to a simulated distribution of female share.[102] First, we produce Monte Carlo simulations in which we randomly re-assign MBA students to sections within their graduating class, taking the number of sections and graduating years from the actual data. Second, we regress the share of female students on class fixed effects in both the actual and the simulated data and collect the residuals. We replicate these two steps 1,000 times. We plot the simulated residuals from this random assignment alongside the residuals from the actual data in Appendix Figure A5. From both a visual inspection and a two-sample KolmogorovSmirnov test, we show that there

[102]Note that these residuals represent the variation that we exploit in our analysis.

is no statistically significant difference between the actual and the simulated distribution, consistently with as-good-as-random assignment of the share of female peers. Also note that, across these 1,000 replications, the median standard deviation is 0.041 with a 90% empirical confidence interval of [0.034, 0.046]. This confidence interval amply contains the within-class standard deviation of 0.043 observed in the actual data.

K Main Results – Additional Evidence

K.1 Effects on Firm Choice

In this section, we explore whether female peers lead women to choose different types of firms that can help explain the results for senior management. For example, women may now enter smaller or lower-paying firms, where they may be more likely to receive a higher job title but this may not reflect a promotion in terms of responsibilities or compensation.

Appendix Table A11 shows the effect of female share on holding a senior management position in a small (1-200), medium (200-4,999), or large firm (5,000+). We find a positive and significant effect on the probability of holding a senior management position in both small and big firms (Columns (1) and (3), respectively) and no significant effect for medium size firms. Although the coefficient is higher for big firms than for small firms, we can not reject the null hypothesis of equality. This suggests that women do not become senior managers disproportionately more in smaller firms.[103] Turning to whether female peers influence the choice of firm throughout the career path, Appendix Table A13 shows that there are no overall changes in employment across the different firm sizes for women. These results suggest that moving to firms of different sizes is unlikely to be a key mechanism for the main results.

We next explore whether our main results can be explained by shifts into different types of firms along the compensation dimension. Appendix Table A12 presents the results for holding a senior management position in a firm with average annual total compensation above or below the median. The magnitude of the coefficients are similar across the two types of firms albeit imprecisely estimated. We also do not find a statistically significant difference in effect sizes (p-value of the difference is 0.656 as reported in Appendix Table

[103]See Appendix Table A28 for the p-values from the tests of pairwise differences across the different specifications. In particular, the p-value for senior managers in big versus medium firms is 0.0881, while the p-value for senior managers in big versus small firms is 0.218.

A28). This also holds when we study the analogous results using compensation for senior managers in Columns (3) and (4). This suggests that women are not more likely to be senior managers in lower-paying firms. Finally, we study whether there is an effect on average firm-level compensation throughout the career path. In Appendix Table A14, we also find no changes in average total annual compensation or on average total annual compensation for senior managers.

K.2 Effects on Profit and Loss (P&L) Responsibilities

We then investigate whether female peers affect the type of functions performed by women. Specifically, we focus on Profit and Loss (P&L) responsibilities.[104] There are two potential explanations for why changes in P&L responsibilities can explain the overall increase in senior management.

First, because P&L responsibilities have been shown to be important for promotions into top management positions, female peers may help women obtain senior managerial positions by encouraging them to take on roles with P&L responsibilities earlier in their careers. As a result, we would observe an increase in P&L job functions. Second, an alternative story would be that women achieve higher rates of senior management in non P&L functions such as administration or human resources. Hence, they are promoted into senior management but are unlikely to progress into top executive positions. This story would be consistent with a decrease in holding P&L positions. Appendix Table A15 shows a positive and significant effect on holding a managerial position in a P&L role (Column (1)) but no significant effect on performing P&L functions (Column (2)). Therefore, these results suggest that female peers lead to an increase in senior managers that is associated with an actual increase in responsibilities.

K.3 Additional Outcomes

In this section, we present results for four additional management outcomes. First, in Appendix Figure A6 we show the results when we use as outcome variable "ever holding a senior management position," which is an indicator variable that takes value 1 if the individual has held a senior management position in that year or any year before and 0 otherwise. We observe an increase in the entry rate into senior managerial positions beginning in the first

[104] Appendix Section B provides details on how we identify job functions.

year after graduation and persisting for at least 15 years, suggesting that a larger network of female peers leads to new entries into senior management.[105] Second, in Appendix Table A53, we show that the positive effect of female peers translates into 0.09 (=0.434/4.968) additional years (or approximately 1 month) spent in senior managerial positions for a 4 percentage point (1SD) increase in female share. Third, Column (1) in Appendix Table A54 shows that, among those who eventually end up becoming a senior manager, there is a decline in years to first position as senior manager of 6.8% (=0.335/4.940) for women.[106] Finally, we find that female peers increase the number of senior management positions held by women (Column (2) in Appendix Table A54).[107] Specifically, a 4 percentage point (1SD) increase in female share increases the number of positions by 4.8% (=.054/1.126). Finally, we show in Appendix Table A55 that the increase in senior managers come from both external and internal promotions. Although the coefficient is larger for external promotions, we can not reject the null hypothesis of equality.[108] This suggests that female peers may help women attain senior management positions in several ways. For example, women may benefit from job referrals provided by female peers or information about which firms hire female senior managers at a higher rate. Moreover, female peers may help women acquire specific skills, such as negotiation, to succeed in the hiring process. Finally, female peers may provide women with information and skills to better navigate the internal promotion process within a firm.

0

L Nonlinear Peer Effects Estimation

In this section, we describe in detail the estimating equation for the nonlinear peer effects results. Specifically, we use a one-knot linear spline and we estimate:

$$\begin{aligned} y_{ikct} =& \beta_1 \overline{FemaleShare}_{-i,kct} + \beta_2 \overline{FemaleShare}_{-i,kct} \times I(\overline{FemaleShare}_{-i,kct} > 0.34) \\ &+ \sum_{j=0,1} (\delta_c + \phi_t + \omega_{ct}) \times I(Female_i = j) + X_{ikct}\gamma' + \epsilon_{ikct} \end{aligned} \tag{A3}$$

[105]The corresponding regression estimates are presented in Appendix Table A9.

[106]Note that this regression is estimated at the individual level instead of using the pooled sample.

[107]Note that this is not restricted to individuals that eventually become managers.

[108]See Appendix Table A28 for the p-values from the tests of pairwise differences across the two specifications. The p-value for senior manager in case of external versus internal promotions is 0.195.

where y_{ikct} is the outcome of interest for individual i in section k from graduating class c in year since graduation t. $\overline{FemaleShare}_{-i,kc}$ is the proportion of female peers of i in section k and graduating class c. The specification also includes a series of class fixed effects (δ_c), year fixed effects (ϕ_t), class-by-year fixed effects ($\omega_{i,ct}$), and their interactions with the gender dummy. The term X_{ikct} includes all the controls listed for equation (1).[109] β_1 is the effect of a marginal increase in female share in sections with a share of female peers below the median (34%). β_2 represents the change in slope for sections with female share above the median.

L.1 Robustness Checks

We present a series of robustness checks to provide supporting evidence that our results credibly identify the causal effect of female peers on senior positions for women.

Missing Data

As shown in Appendix Table A18, the match rate is not perfect across all the datasets and this may introduce bias to our estimates if missing data is systematically correlated with our treatment variable, share of women in the section. In Appendix Table A19, we investigate whether unmatched observations from each of the dataset are systematically correlated with female peers. We report the regression results from estimating equation (1) where the dependent variable in each column is a dummy if the individual is matched to the specified dataset.[110,111] We do not find a correlation between female share and being in the sample in any case. This provides strong evidence that selection into the sample cannot explain our results.

Alternative Definitions and Samples

We also conduct a series of robustness checks using alternative definitions and samples. Results are summarized in Appendix Figure A12 and in Appendix Table A22. First, we

[109]Note that for simplicity, we did include the interactions with the female dummy when writing equation (A3). However, the estimation is performed by fully interacting the regressors with the female indicator.

[110]Note that we do not include controls beyond gender, class and year fixed effects, because additional information is not available for unmatched individuals.

[111]Because this analysis requires microdata and we do not have individual data for the full census of MBA graduates prior to 2011, we use the alumni directory records as a proxy for the sample universe in Columns (1) and (2). That is, missing dummy equals 1 if in the alumni directory records and 0 otherwise. In Columns (3) and (4), we use the matched LinkedIn and administrative data to conduct the analysis for the 2011-2018 cohorts.

use an alternative definition for nonemployment. In our main analysis, we consider only nonemployment breaks between consecutive positions. However, there are some individuals whose last position ends before the date we obtained the profiles in 2019. Because it is unclear whether the individual is truly not employed or simply has not updated their profiles, we do not consider these spells as nonemployment in the main definition and do not include these observations in the analysis. As a robustness check, we assume that all these time periods up to 2019 are nonemployment spells and re-estimate equation (1) for senior management. We show in Appendix Figure A12 and Column (2) that the main result is robust to the use of this alternative nonemployment measure.

Second, since our sample includes people graduating from 2000 to 2018, we do not observe everyone for up to fifteen years. Therefore, our sample is not balanced over time. As a robustness check, we estimate the coefficients from regression (1) on our main outcome variable restricting the sample to people we can follow throughout the fifteen years post-graduation. Appendix Figure A12 and Column (3) show that the results obtained using this balanced sample are consistent with our main findings.

Third, to correctly interpret the results and infer meaningful policy implications, it is valuable to understand whether they are driven by outliers. To shed light on this, we drop from the sample the observations in sections with a proportion of female students in the first and last percentile of the female share distribution. We then re-estimate equation (1) on this new sample. Appendix Figure A12 and Column (4) show that the effect of female peers is still positive and significant when we apply this sample restriction.

Fourth, our main definition of managers does not include entrepreneurs or founders as we are interested in analyzing the effects on self-employment separately from management. We show in Figure A12 and Column (5) that the inclusion of entrepreneurs in the definition of senior managers does not change the results.

Finally, we check whether our main results hold when we restrict the analysis to the observations for which we have information on industry and level of female-friendliness of the firm, as defined in Section 3.3. In Appendix Figure A12 and Columns (6) and (7), we show that the results are consistent albeit noisier for these subsamples of observations.

Placebo Test: Random Re-assignment of Sections

Following the methodology described in Athey and Imbens (2017), we conduct a randomization test in which we randomly re-assign students to sections within the same class. The re-assignment is performed without replacement and using uniform probability. We conduct this re-assignment 1,000 times and, in each iteration, we estimate our coefficient of interest from equation (1) for our main outcome variable, probability of holding a senior management position, for both men and women. In Appendix Figure A11, we plot the distributions of the placebo treatment effects for men and women, respectively. The vertical lines indicate the actual coefficients we estimated using the true section assignment. As shown in the figure, the true effect for men falls within the distribution of placebo effects, consistent with the null effect on men that we find in our main results (Section 5.2). On the contrary, the estimated true effect for women is much larger than any of the placebo effects, providing supporting evidence that the estimated impact of female peers on women's probability to become senior managers is unlikely to have occurred by chance.

Placebo Test: Pre-MBA Years

If female share in each section is exogenous, it should have no effect on our outcome variable in the years prior to the MBA, when peer groups have not been formed yet. Appendix Table A20 shows the coefficients from regression (1) estimated separately for up to three years before the start of the MBA program. We find no consistent evidence of an effect of female share on female future graduates, supporting our identification strategy.

Robustness to Alternative Controls

In Table A21, we show that our estimates are robust to alternative sets of controls. Column (1) reports the estimates from the baseline specification. In Column (2), we only control for class fixed effects, year fixed effects class-by-year fixed effects, as well as their interactions with a female dummy. Then, in Column (3), we also include stratification variables as controls. Lastly, in Column (4), we add individual level-characteristics as described in Section 5.1.[112] Across all specifications, we show that female peers have a significant and positive effect on career advancement of women with no corresponding effects on men.

Clustering at the Class Level

In Section 5.1, we implement two randomization tests to show that the assignment of students to sections is as good as random. In the second test we performed following Caeyers and Fafchamps (2021), the estimation is done clustering at the class level. On the contrary, in our main empirical strategy, we cluster at the section level as in Guryan et al. (2009). In

[112]Note that for all of the controls we include, we also include missing indicators and all of their interactions with a female dummy.

this section, we show that our estimates are robust to clustering at the class level. Appendix Table A23 shows the coefficient of interest from estimating equation (1) when clustering at the section level (Column(1)) and when clustering at the class level (Column(2)). The two clustering levels lead to almost identical results.

Logistic Model

Finally, given that our main outcome variable is the probability of holding a senior management position, we show that our results are robust when we use a conditional logit model instead of OLS. Appendix Table A24 reports the coefficients from our main specification in Column (1) and from the logistic specification in Column (2). We find that with this alternative model the effect of female peers is positive and significant at the 3.4% level. The marginal effect is 0.477 which translates into a 4.9% increase in the probability to be a senior manager for a 4 percentage point (1SD) increase in the female share distribution.

M How Do Female Peers Lead to an Increase in Female Senior Managers?

M.1 Effects on Attachment to the Corporate Pipeline

In this section, we investigate whether our results are driven by an increase in the labor market attachment of female MBAs, an increase in their entry rates into the management pipeline, or a decrease in entrepreneurship.

Labor Market Attachment

An extensive literature has highlighted that a key explanation for the large gender gap in labor market outcomes is differences in labor supply, such as weekly hours worked, full-time or part-time status (Bertrand et al., 2010), and career interruptions (Bertrand et al., 2010; Kleven et al., 2019). Moreover, these differences likely translate into differences in promotion probabilities into management roles. Therefore, one potential explanation for the increase in the likelihood of becoming a senior manager may be the increase in labor market attachment.[113] For example, female peers may provide useful information on childcare availability

[113]Note that, while we do not have childbirth information, we are able to infer employment and career breaks based on the dates listed on CV.

or advice on how to balance work and family.

Contrary to this hypothesis, in Appendix Table A25, we find no effects of MBA female peers on employment (Columns (1)) or on the total number of months in non-employment (Column (2)). Given that we observe an increase in senior management unconditionally on employment, this result highlights that changes in employment cannot explain the increase in senior management. Indeed, when we condition the sample to only those who are employed, we find a very similar magnitude in the effect size in Column (4) compared to the main results presented in Column (3). It is worth noting that career breaks may not be listed on the CV if they are temporary leaves of absence from the firm and the worker remains attached to it, such as the case of parental leaves. As a result, the CV data are likely to be an underestimate of the true number of career breaks. For example, the average cumulative number of months in nonemployment inferred from the CV data is 2.3 months at the end of 9 years, compared to 6.8 months Bertrand et al. (2010) documented in their sample of MBA graduates.[114] However, as we show in Appendix Figure A20, we document similar trends as what has been shown in the literature for the gender difference in months of career breaks.

Effects on Entry Rate into Management Pipeline

In addition to effects on labor supply, female peers may encourage women to seek out more management positions, which can explain the increase in senior management that we observe. Appendix Table A26 shows that a higher share of female peers does not lead to an increase in the likelihood of ever holding any managerial position, for example, by increasing the likelihood of women entering first-level managerial positions. This suggests that the increase in female senior managers is not driven by more women entering the managerial pipeline.

Effects on Entrepreneurship

Bertrand et al. (2010) document that women are more likely than men to work part-time or lower hours when they are self-employed. For example, after ten or more years post-MBA, 62 percent of self-employed women work part-time compared to only 15 percent of self-employed men (Bertrand et al., 2010). The fact that women who want to work part-time disproportionately employ themselves suggests that entrepreneurship may be used by women to find a better balance between work and family life.

The increase in female senior management may be explained by female peers helping

[114]See Table 1 of Bertrand et al. (2010).

women, who otherwise would have moved into self-employment, remain attached to their firm. To test this hypothesis, we estimate the effect of female peers on the probability of becoming an entrepreneur. Appendix Table A27 shows a negative but not significant effect. Note also that entrepreneurs represent less than 4% of our sample. This evidence suggests that, even if we can not fully rule out this story, a reduction in self-employment does not seem to be a key driver of our results on senior management.

M.2 Male-Dominated Industries

We have shown that female peers help women achieve senior management positions. One hypothesis is that these effects would be magnified in settings where women are underrepresented and where female MBAs may rely more on their MBA networks. As shown in Appendix Figure A3, there exists substantial gender variation in industry choice. Compared to consumer goods and healthcare, female MBAs are less likely to enter the three male-dominated industries (finance, tech and consulting) post graduation. We test this hypothesis by studying whether the results are driven by male-dominated industries. We will show that the increase in senior managers is driven by higher rates of promotion for women in male-dominated industries with no corresponding shifts in employment towards these industries.

Senior Managers in Male-Dominated Industries

The effect of female peers in male-dominated industries is theoretically ambiguous. On one hand, female peers may be important in helping women enter and succeed in male-dominated industries. Recent papers have shown that female peers help women persist in male-dominated fields such as STEM (Bostwick and Weinberg, 2018). In a more male-dominated industry, women may also face additional barriers in accessing the informal "old boys' club" job networks (Cullen and Perez-Truglia, 2019). Therefore, a larger network of women may represent an important substitute for these networks and help women access advice and information channels that they would not have access to otherwise. On the other hand, more female classmates may encourage women to enter more stereotypical female sectors, as has been found in educational settings (Brenoe and Zolitz, 2020). Because female MBA peers are more likely to be represented in female-dominated industries, the referrals and career advice provided by these peers may only be relevant for those in female-dominated industries. As a result, we may expect a larger effect of female peers in these industries.

Appendix Table A16 reports the estimates for holding a senior management position in a male-dominated industry (Column 1) and in a female-dominated industry (Column 2).[115] We show that a 4 percentage point (1SD) increase in female share leads to a 12% (=0.024/0.201) increase in the probability of becoming a senior manager in a male-dominated industry. On the contrary, we find no effect on the probability of becoming a senior manager in a female-dominated industry.[116] The difference between the two coefficients of interest is significantly different at the 3% level.[117]

Entries vs. Promotions

What explains the increase in senior managers in male-dominated industries? This increase can be driven by a combination of higher likelihood of women entering these industries and higher promotion rates of women within these industries. In Column (3) of Appendix Table A16, we show the effect of female peers on working in a male-dominated industry. We find that there is no significant effect on entries into male-dominated industries.[118] Notably, this result stands in contrast to prior gender peer effects papers that find a significant relationship between female peers and the choice of female students to enter in male-dominated fields of study such as STEM (Brenoe and Zolitz, 2020). The difference in this setting may result from the fact that MBA graduates enter the program with five years of work experience on average and, as a result, are less influenced by their peers in the choice of industry.

These results provide suggestive evidence that the increase of senior managers in male-dominated industries is driven by higher promotion rates of women in these industries. In Appendix Table A30, we conduct an exploratory analysis in which we investigate the impact on senior management while restricting the sample to individuals that are working in male- or female-dominated industries. As hypothesized, we find a positive and significant effect when we condition on working in a male-dominated industry, suggesting a higher treatment effect of female peers in this sample. It is, however, important to acknowledge that even if female peers do not influence the entry rate across different industries, this analysis likely suffers

[115] Male-dominated industries are consulting, tech, and finance. Female-dominated industries are consumer goods and healthcare.

[116] Appendix Figure A13 plots the dynamic version of our results.

[117] See Appendix Table A28 for the p-values from the tests of pairwise differences across the two specifications.

[118] Given that the coefficient is imprecisely estimated, we provide two additional pieces of evidence against an effect on industry choice. First, in Appendix Table A29, we present the analogous results for each industry separately. We find no overall effect of female peers on industry choice. Second, Appendix Figure A14 shows the dynamic effects for entries in male-dominated industries. Consistent with our pooled results, we do not find a significant effect in any of the post MBA years included in our analysis.

from a selection problem to the extent that female peers affect the composition of women that enter these industries. For example, female peers may influence high-ability women to enter male-dominated industries and low-ability women to enter female-dominated industries.[119] This would be consistent with this pattern of results.

M.3 Results on Female-Friendly Firms Using Alternative Measures

In Appendix Figure A21 and Appendix Table A56, we present additional results on the effects of female peers on senior management in female-friendly firms using alternative measures. These include firm rating from FairyGodBoss (FGB) (Columns 1-2), weeks of paid maternity leave (Columns 3-4), percentage of board members that are female (Columns 5-6), firm-level gender gap in compensation (Columns 7-8), and gender gap in compensation for senior managers (Columns 9-10). Consistent with our main results, we find a significant effect on most of these measures.

M.4 Female-Friendly Firms and Male-Dominated Industries

In this section, we investigate whether the findings on female-friendly firms can explain the increase in senior managers in male-dominated industries. For example, the advancement of women in finance, tech and consulting may be driven by better knowledge or increased access to firms that are more supportive of women as a result of their female MBA peers.

In Appendix Table A36, we test this hypothesis by investigating the probability of becoming a manager in a female-friendly firm versus a non-female-friendly firm when restricting to male dominated industries. Consistent with the results in Section 6, the magnitude of the coefficient for achieving a senior management position in a female-friendly firm is much larger than the corresponding coefficient for non-female-friendly firms. Indeed, the two coefficients are statistically different from each other at the 9% level. This provides suggestive evidence that, indeed, the overall effect on male-dominated industries can be explained by

[119] However, notice that this composition effect cannot fully explain the main results given that we do not find a negative effect on female senior managers in female-dominated industries. This means that, there must exist complementarities between the women who enter male-dominated industries and these industries.

female-friendly firms.[120]

N Explaining the Gender Differences in Compensation

In this section we explore what explains the gender gap in imputed compensation. Appendix Table A57 presents coefficient estimates from regressing total annual compensation on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and additional controls using the pooled sample of all individual-year observations. The female coefficient represents the gender gap in total compensation. We find that a substantial portion of the gender gap can be explained by industry choice, suggesting that male MBAs are more likely to enter more lucrative industries. The gender gap further shrinks when we include the broad managerial category (non-manager, first-level, or senior manager). This captures the fact that men are more likely to be in senior management positions. Notably, even after controlling for management level, the gender gap in compensation does not close completely; we move from a 33% gender gap in Column (1) to a 21% gender gap in Column (7). Since the imputation is based on current firm, broad managerial category, and gender, this may indicate that women may be sorting into firms that are lower paying in general. We will provide evidence on whether the gender gap in imputed compensation closes as a result of female peers.

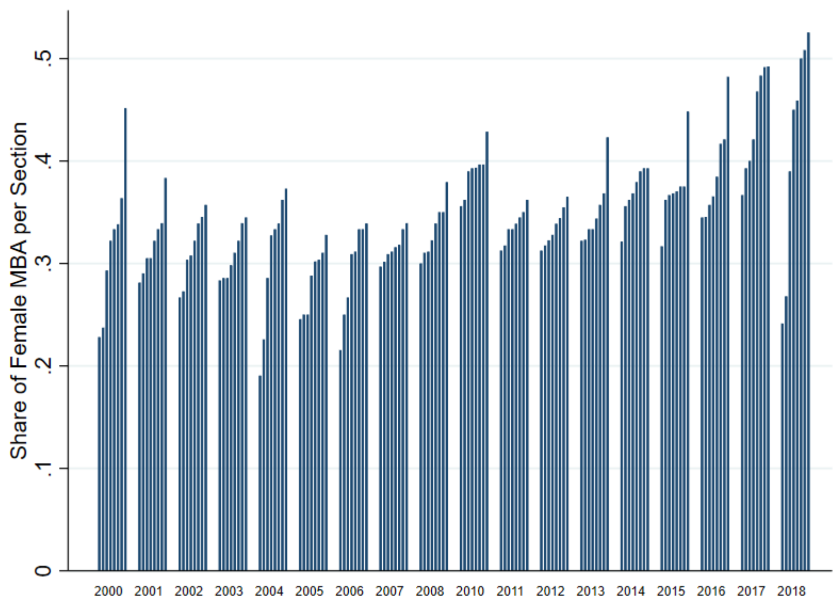
[120] This analysis is conditioning on an outcome, that is working in a male dominated industry. We previously showed that there is no effect of female peers on this outcome. Moreover, results hold when we look at the probability of being a senior manager in a male-dominated industry *and* a female-friendly firm versus a non-female-friendly firm (Appendix Table A37). Analogous results for female-dominated industries are in Appendix Table A38.

O Appendix Figures and Tables

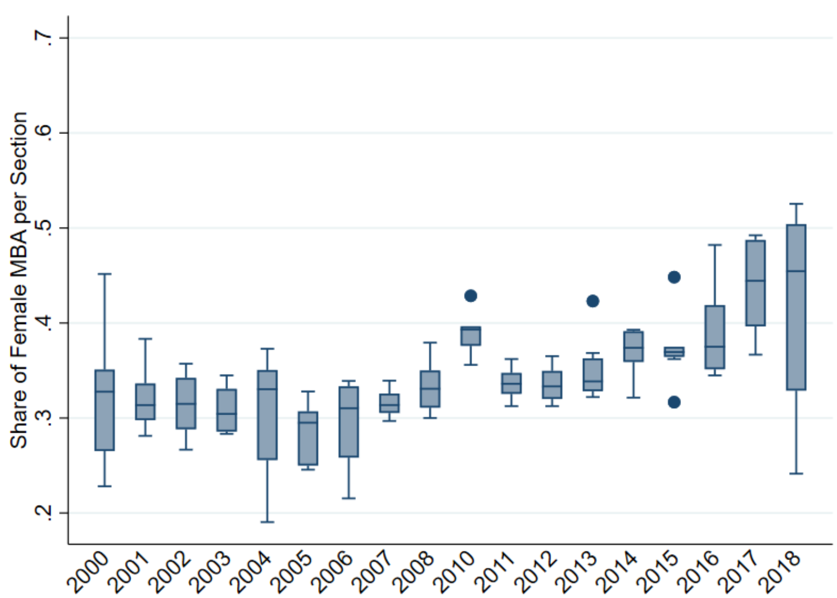
Appendix Figures

Figure A1: Distribution of Female Share across Sections by Graduating Cohort

(a) Histogram

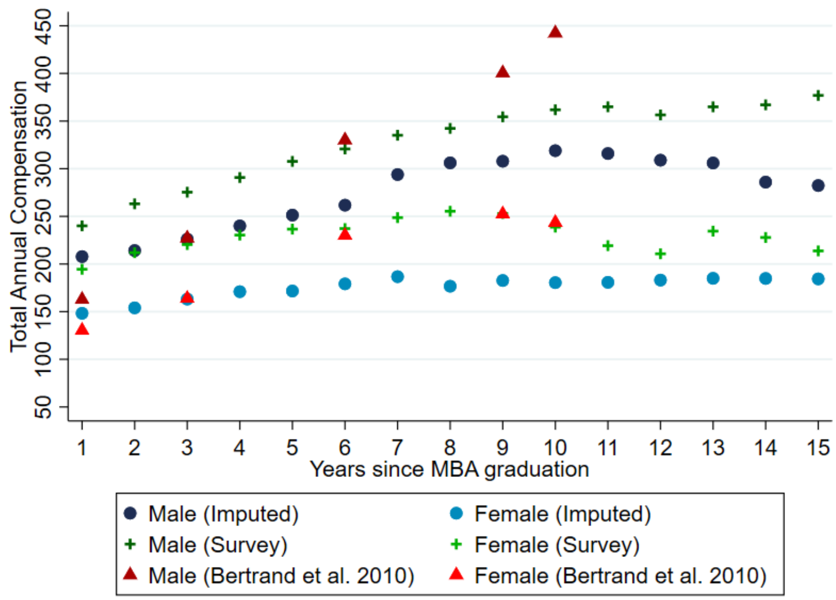


(b) Boxplot



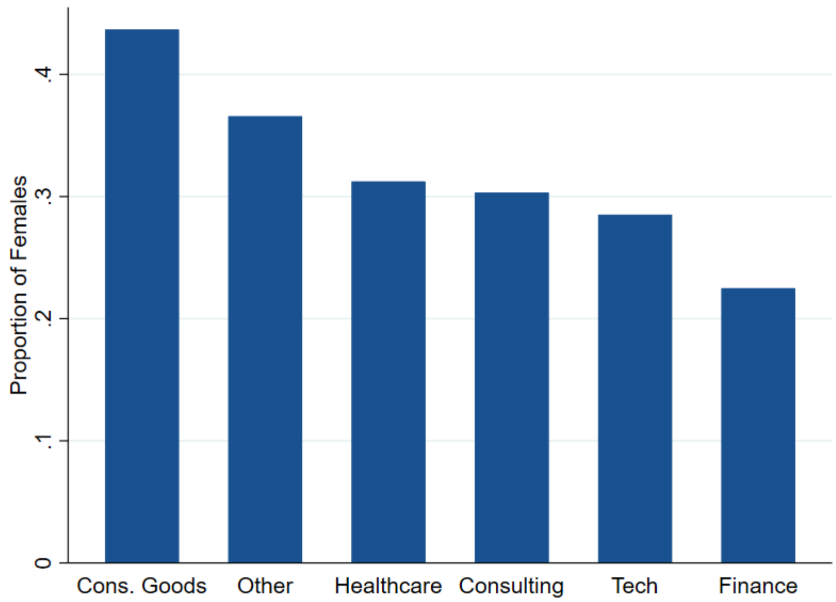
Notes: In Figure A1, we plot the share of female MBA graduates per section and graduating year. In Figure A1b, we plot the boxplot of share of female MBA graduates by graduating year. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure A2: Comparison of Imputed Total Compensation with Alternative Sources



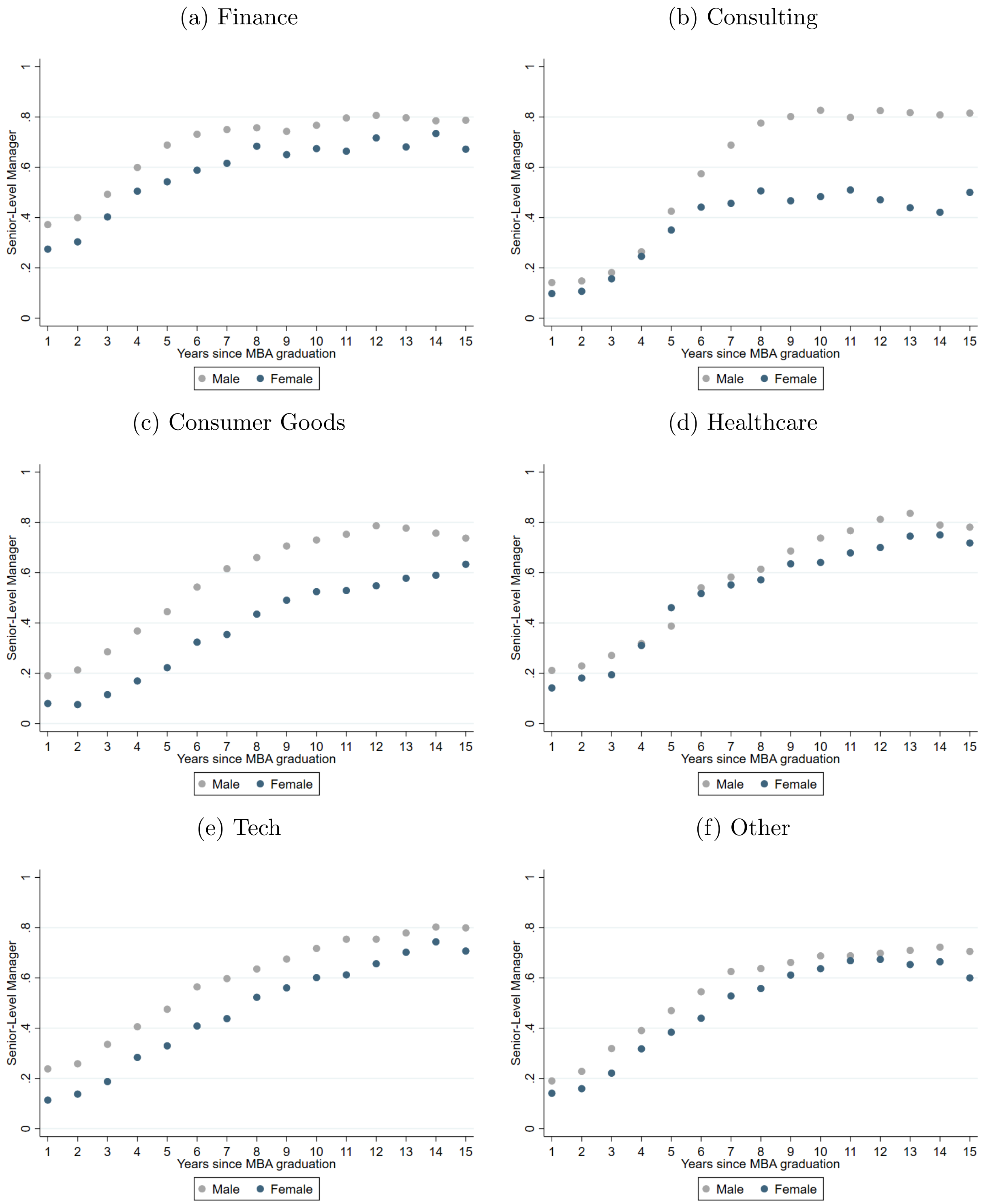
Notes: We plot the total compensation for men and women from three data sources: (i) Glassdoor data (imputed measure based on firm, gender, and management position); (ii) survey data, and (iii) Bertrand et al. (2010). Glassdoor sample includes students of the graduating classes 2000-2018, excluding 2009. Survey sample includes students of the graduating classes 2000-2015, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure A3: Female Representation by Industry



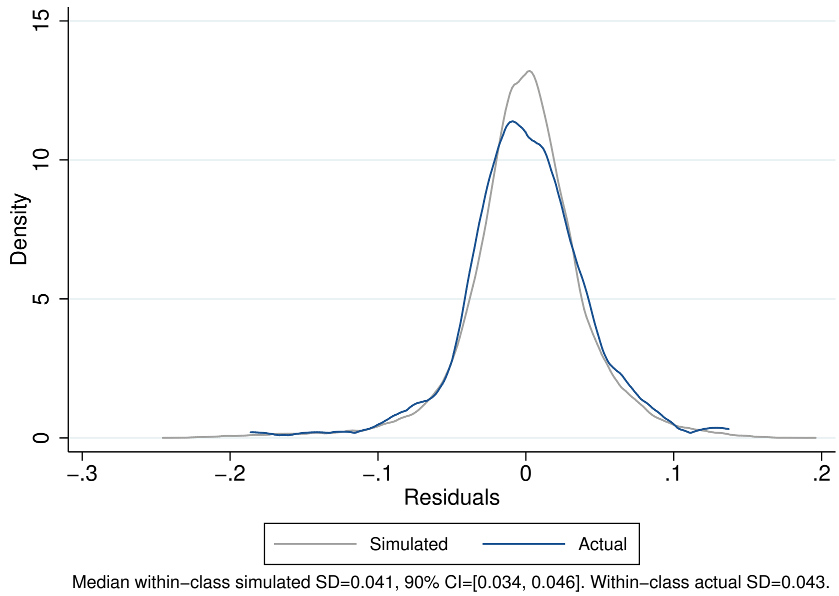
Notes: We plot the share of female employees by industry. Sample includes students of the graduating classes 2000-2018, excluding 2009. Survey sample includes students of the graduating classes 2000-2015, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure A4: Probability of Holding a Senior Management Position by Industry



Notes: We plot the percentage of male and female graduates who are holding a senior managerial position by industry over time since graduation (analogously to Figure 2). Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure A5: Distribution of Residualized Actual and Simulated Female Share



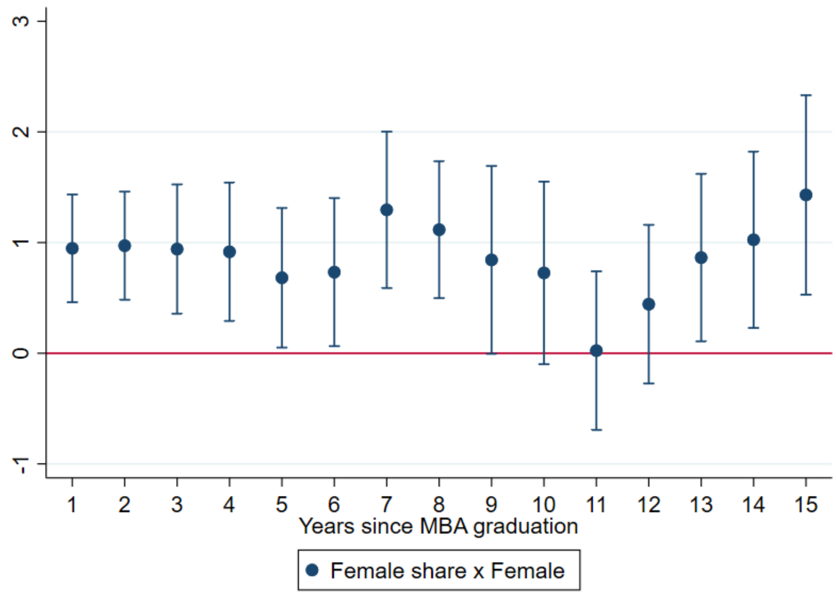
Notes: We plot the actual and simulated share of female MBA graduates per section residualized by graduating year. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure A6: Effect of Female Peers on Senior-Level Management Positions

Figure A7: Effect of Female Peers on Ever Holding Senior-Level Management Positions

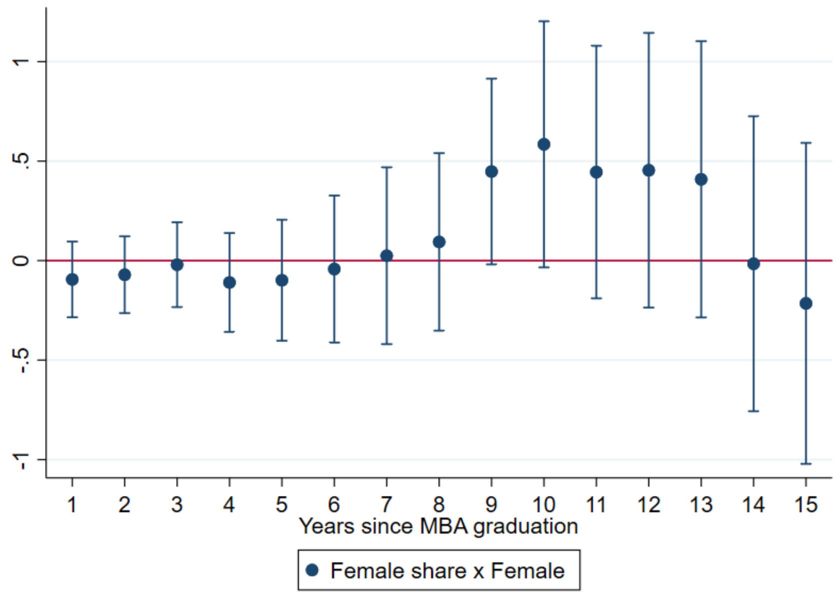
Notes: We plot the coefficients for men and women and their 95% confidence intervals from estimating equation (1) separately for each year since graduation. Refer to Figure 5 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure A8: Effect of Female Peers on Holding Director and VP Positions



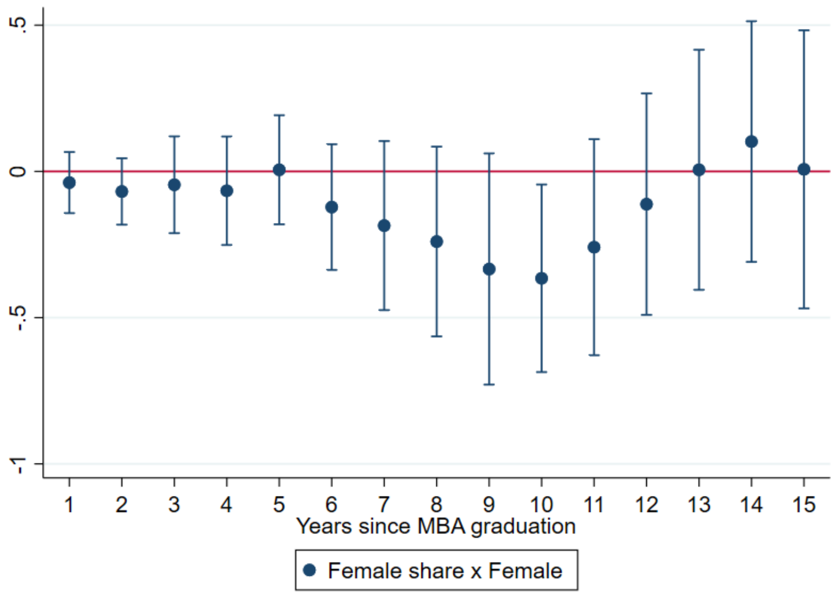
Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. Refer to Figure 5 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure A9: Effect of Female Peers on Holding SVP Positions



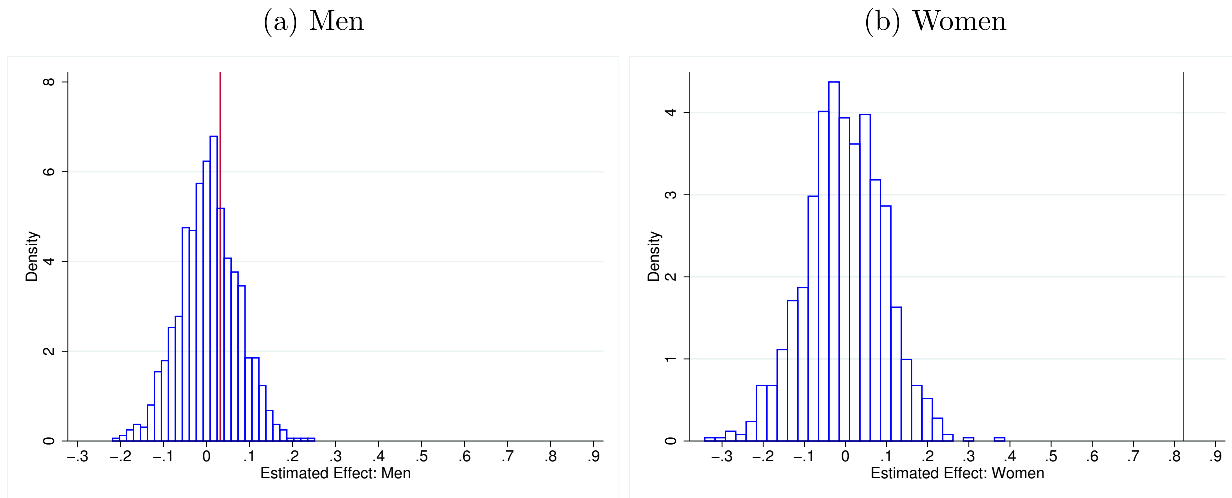
Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. Refer to Figure 5 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure A10: Effect of Female Peers on Holding C-level Positions



Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. Refer to Figure 5 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure A11: Effect of Female Peers on Holding Senior Management Positions Using Placebo Sections

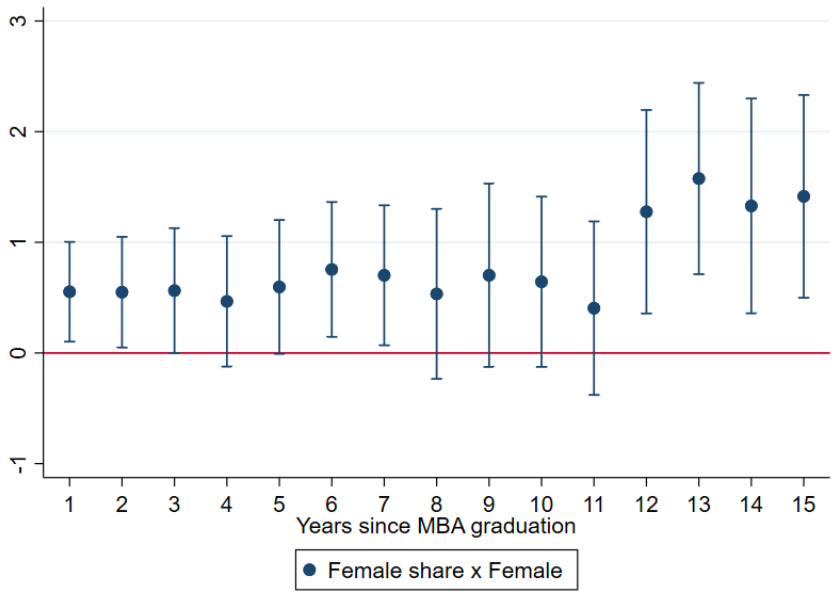


Notes: We plot the distributions of the placebo treatment effects computed using a randomization test in which we randomly re-assign students to sections within the same class. The re-assignment is performed without replacement and using uniform probability. We conduct this re-assignment 1,000 times and, in each iteration, we estimate our coefficient of interest from equation (1) for our main outcome variable, probability of holding a senior management position for men and women. The vertical lines indicate the actual coefficients we estimated using the true turn coed dates.

Figure A12: Effect of Female Peers on Senior Management: Robustness Checks

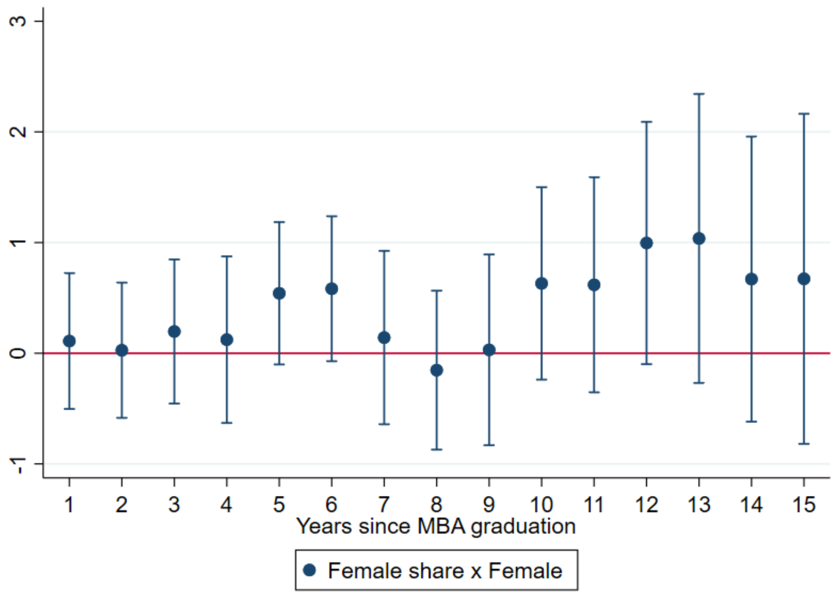
Notes: We plot the coefficients for women from estimating equation (1) pooling together all years since graduation. In all columns, the outcome variable is the probability of holding a senior management position. Each coefficient is the result of a separate estimation from a series of alternative sample restrictions. Refer to Figure 5 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A13: Effect of Female Peers on Holding a Senior Management Position in a Male Dominated Industry by Year Since Graduation



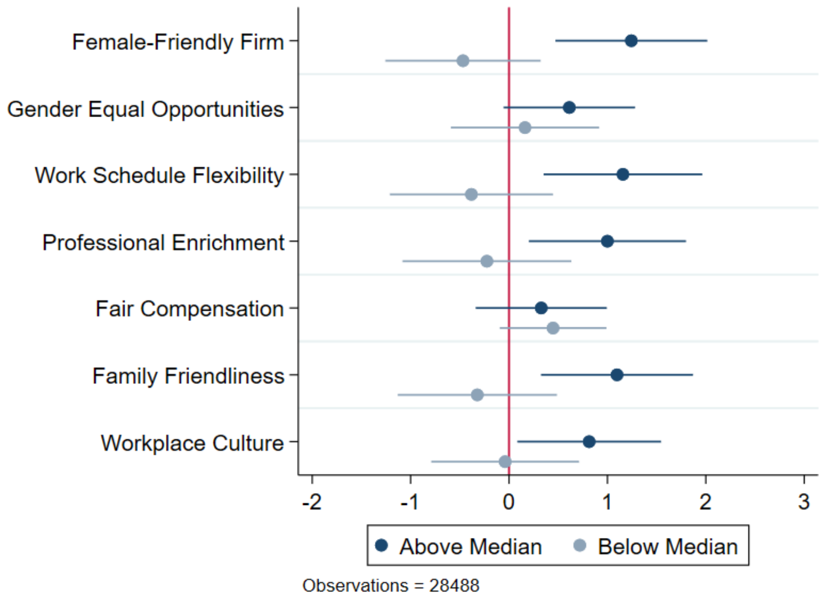
Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. Refer to Figure 5 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure A14: Effect of Female Peers on Working in a Male Dominated Industry by Year Since Graduation



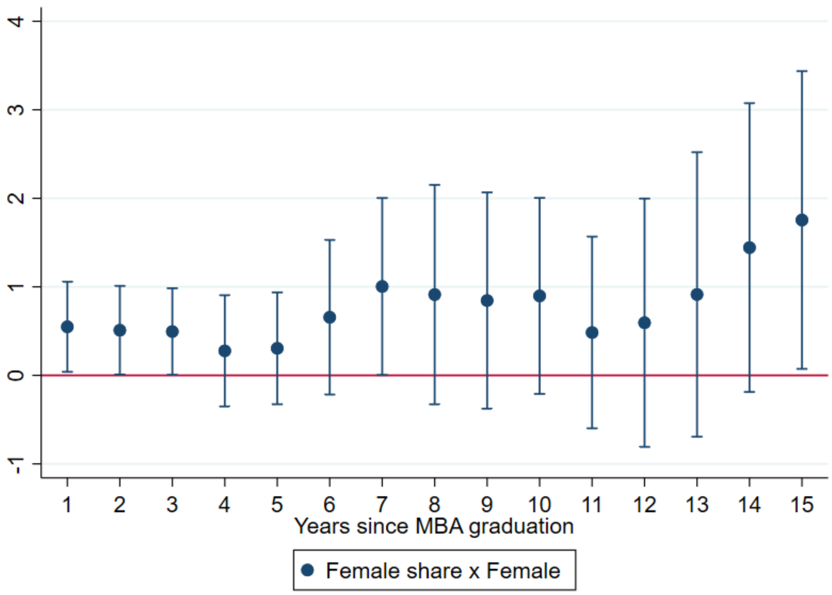
Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. Refer to Figure 5 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure A15: Effect of Female Peers on Senior Management in Female-Friendly Firms



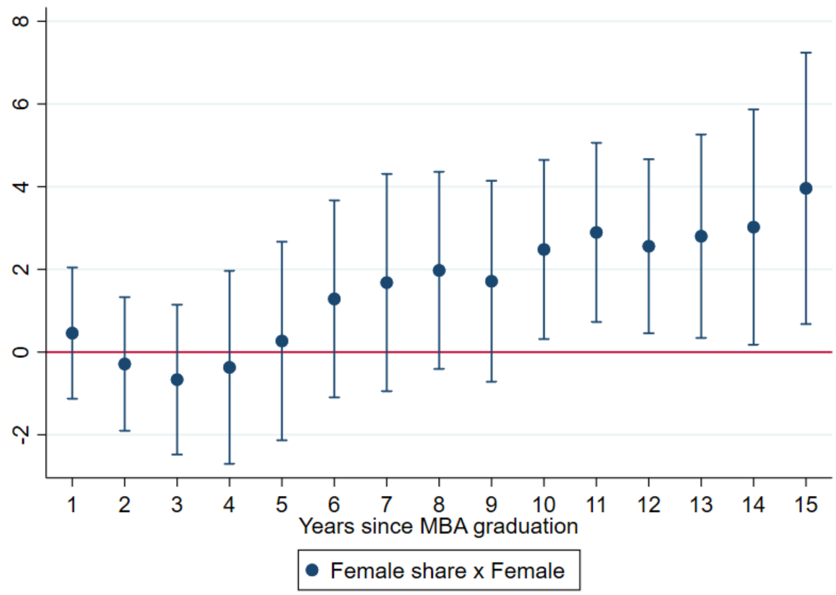
Notes: We plot the coefficients for women from estimating equation (1) pooling together all years since graduation. Each coefficient is the result of a separate estimation where the outcome variable is an indicator of whether the firm is above or below the median in each of the six female-friendly component indices (gender equal opportunities, work schedule flexibility, professional enrichment, family-friendliness, workplace culture, and fair compensation) as well as the overall female-friendly rating. Refer to Figure 5 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A16: Effect of Female Peers on Holding a Senior Management Position in a Female Friendly Firm by Year Since Graduation



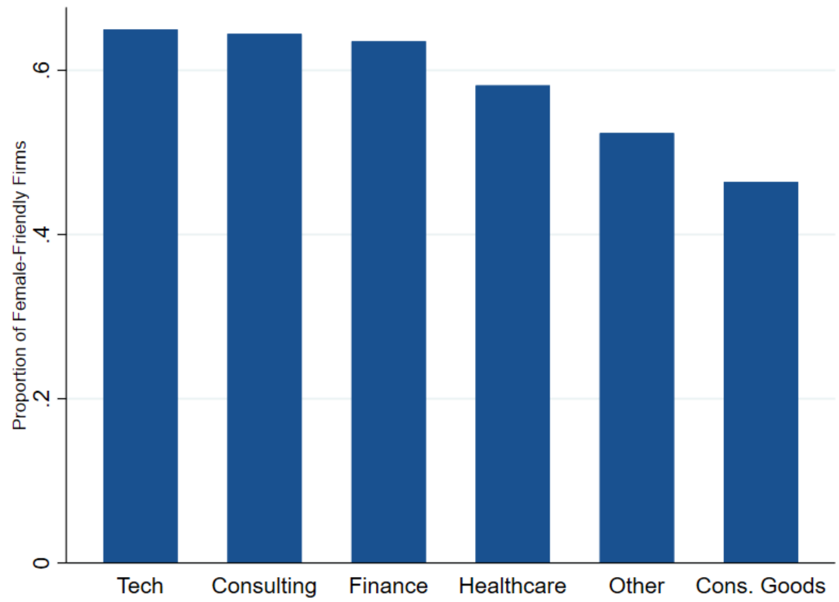
Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. Refer to Figure 5 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure A17: Effect of Female Peers on Working in a Female Friendly Firm by Year Since Graduation



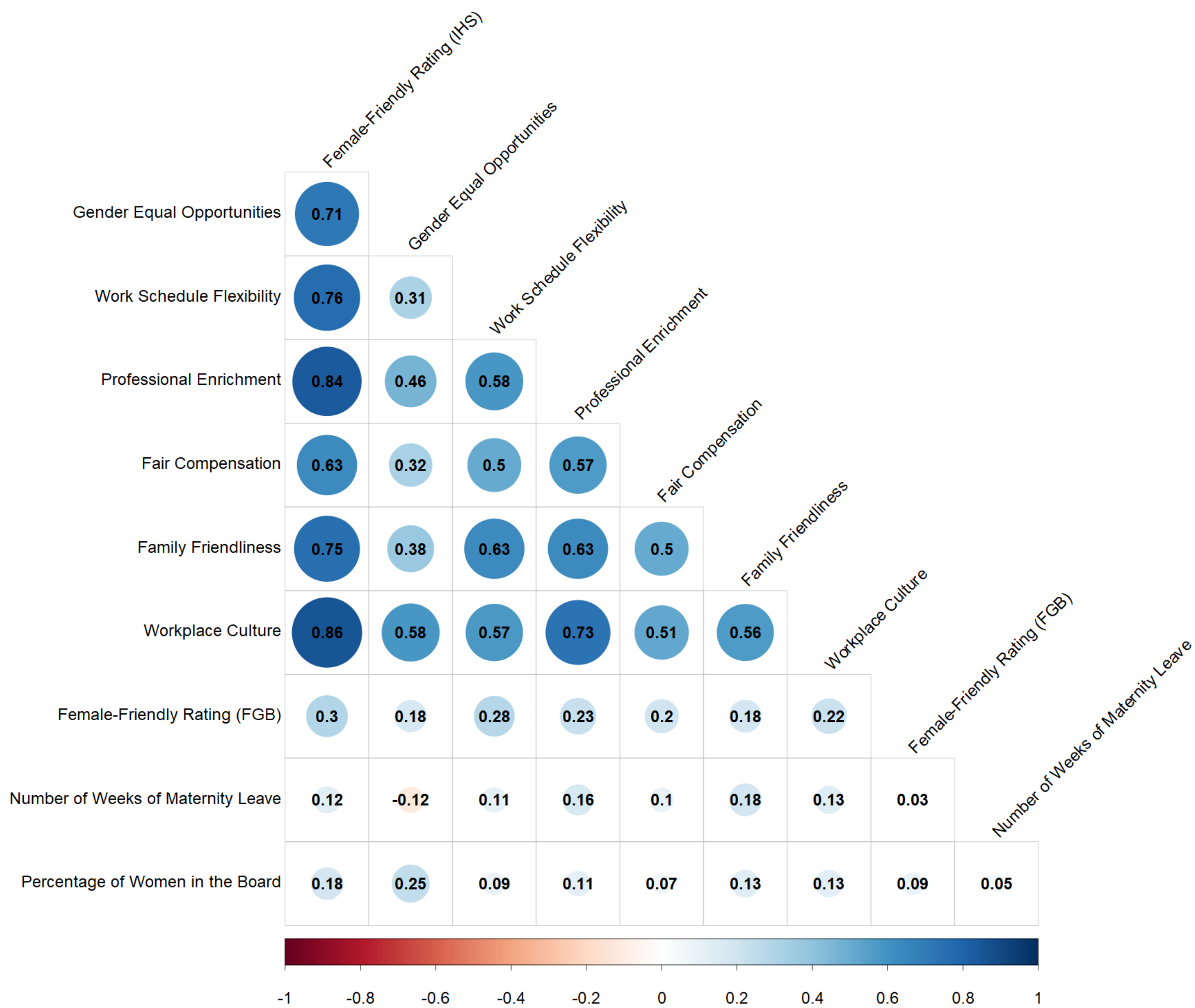
Notes: We plot the coefficients for women and the associated 95% confidence intervals from estimating equation (1) separately for each year since graduation. Refer to Figure 5 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level.

Figure A18: Female-Friendly Firms Representation by Industry



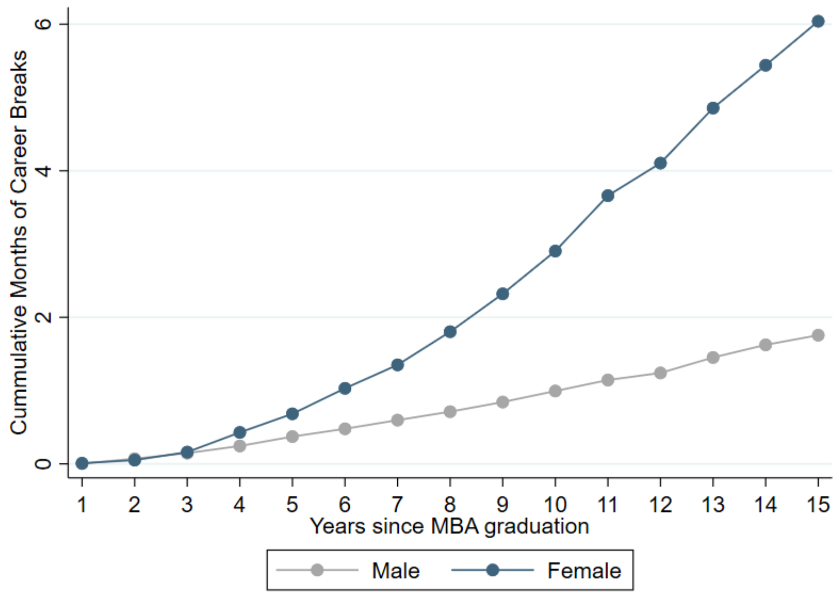
Notes: We plot the share of female-friendly firms by industry. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure A19: Correlation Across Female-Friendliness Measures



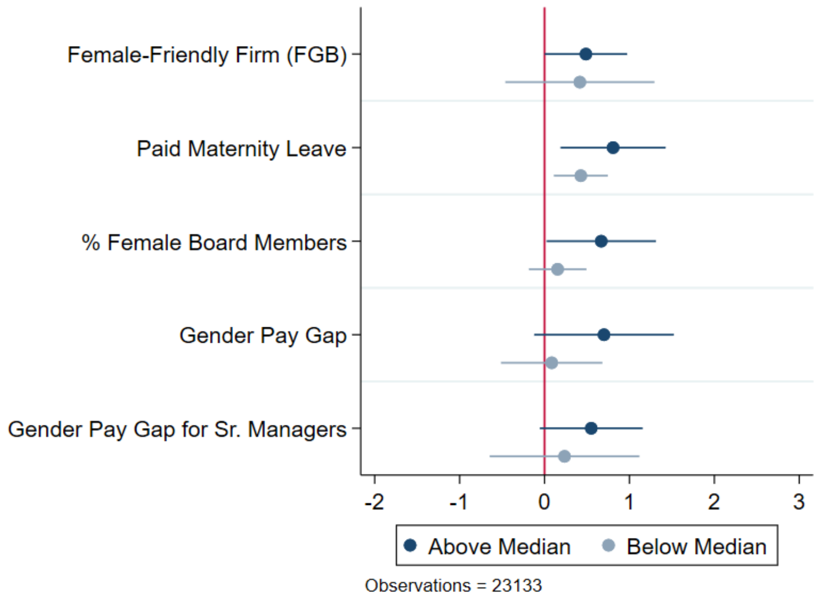
Notes: We plot the correlation between female-friendly measures across multiple dataset: (i) the overall rating and the six standardized indices from InHerSight.com, (ii) the overall rating and number of paid weeks of maternity leave from FairyGod-Boss.com, and (iii) the percentage of female board members from 5050 Women on Board. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Figure A20: Total Months of Career Breaks



Notes: We plot the total months of career breaks for men and women. We define a career break as a gap between the end and start dates of two consecutive positions of at least a 3-month. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

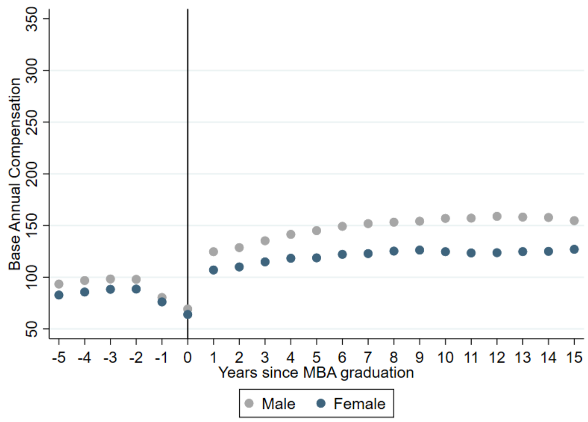
Figure A21: Senior Manager in Female-Friendly Firms: Alternative Measures



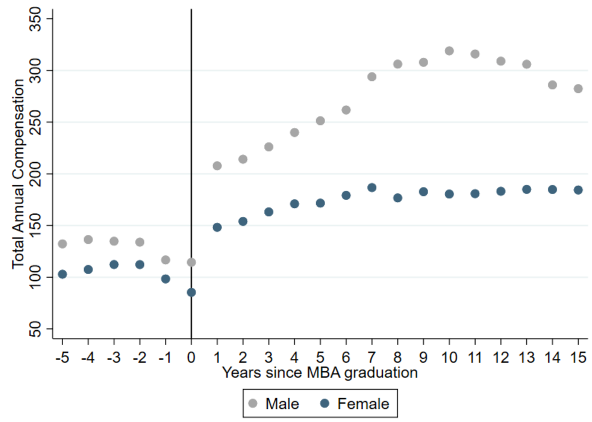
Notes: We plot the coefficients for women from estimating equation (1) pooling together all years since graduation. Each coefficient is the result of a separate estimation where the outcome variable is one of the alternative measure of female-friendly firms: firm rating from FairyGodBoss (FGB), weeks of paid maternity leave, percentage of board members that are female, firm-level gender gap in compensation, and gender gap in compensation for senior managers. Refer to Figure 5 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A22: Compensation (Imputed)

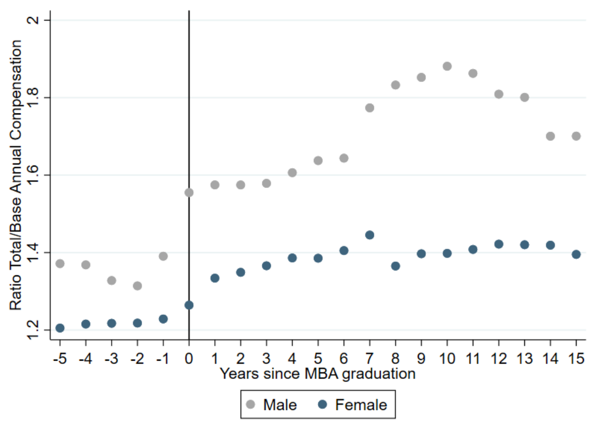
(a) Base Annual Compensation (in $ thousands)



(b) Total Annual Compensation (in $ thousands)



(c) Ratio Total/Base Annual Compensation



Notes: We plot the base annual compensation (Figure A22a), total annual compensation (Figure A22b), and their ratio (Figure A22c) over time since graduation. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation.

Appendix Tables

Table A1: Summary Statistics – Demographics and Pre-MBA Background

	All	Male	Female	Difference p-value in par.
A. Demographics				
Female	0.36			
	(0.48)			
Age	29.88	30.20	29.35	0.85**
	(1.98)	(2.06)	(1.73)	(0.00)
U.S. Citizen	0.65	0.62	0.70	-0.08**
	(0.48)	(0.49)	(0.46)	(0.00)
Race				
White	0.65	0.69	0.59	0.11**
	(0.48)	(0.46)	(0.49)	(0.00)
Asian	0.20	0.17	0.25	-0.07**
	(0.40)	(0.38)	(0.43)	(0.00)
Black / Hispanic	0.13	0.12	0.14	-0.03*
	(0.33)	(0.32)	(0.35)	(0.06)
Other	0.02	0.01	0.02	-0.01
	(0.13)	(0.12)	(0.15)	(0.12)
GMAT	716.45	720.76	709.04	11.72**
	(35.70)	(33.84)	(37.57)	(0.00)
B. Pre-MBA Background				
Pre-MBA Years of Experience	5.00	5.10	4.80	0.30**
	(1.95)	(1.98)	(1.87)	(0.00)
Any Management Experience	0.39	0.38	0.41	-0.02
	(0.49)	(0.49)	(0.49)	(0.13)
Any Senior-Level Management Experience	0.13	0.14	0.12	0.02*
	(0.34)	(0.35)	(0.32)	(0.05)
Average Total Compensation (Imp.) ('000s)	123.35	132.85	106.97	25.89**
	(120.74)	(134.42)	(90.29)	(0.00)
Worked in Male-Dominated Industry	0.63	0.64	0.61	0.03*
	(0.48)	(0.48)	(0.49)	(0.07)
Top 20 Undergrad	0.29	0.27	0.34	-0.07**
	(0.45)	(0.44)	(0.47)	(0.00)

Notes: Summary statistics reported for full sample, male students only and female students only. Standard deviations unless otherwise denoted are reported in parentheses. The last column reports the male-female difference. The p-value of the two sample t-test is reported in parentheses. Data in panel A. Demographics come from the school administrative dataset. Data in panel B. Pre-MBA Background come from the public LinkedIn profile dataset with the exception of (i) average total compensation (imp.), that comes from the Glassdoor dataset, and (ii) top 20 undergrad, that comes from the school administrative dataset. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Summary Statistics – Academic and Career Outcomes

	All	Male	Female	Difference p-value in par.
A. Academic Outcomes (Person Level)				
Overall GPA	3.52	3.54	3.48	0.06**
	(0.27)	(0.28)	(0.27)	(0.00)
Fraction Finance Classes	0.15	0.17	0.12	0.05**
	(0.11)	(0.11)	(0.08)	(0.00)
B. Career Outcomes (Person-Year Level)				
Any Management Role	0.75	0.75	0.75	0.00
	(0.43)	(0.43)	(0.44)	(0.47)
Senior-Level Manager	0.43	0.47	0.34	0.14**
	(0.50)	(0.50)	(0.47)	(0.00)
Employed	0.99	0.99	0.99	0.01**
	(0.09)	(0.07)	(0.12)	(0.00)
Cumulative Months of Nonemployment	0.57	0.40	0.91	-0.51**
	(3.56)	(2.77)	(4.76)	(0.00)
Base Compensation (Imp.) (000's)	133.00	141.53	117.37	24.16**
	(52.00)	(53.18)	(45.82)	(0.00)
Total Compensation (Imp.) (000's)	223.31	253.25	168.42	84.83**
	(315.35)	(371.37)	(155.85)	(0.00)
Male-Dominated Industry	0.59	0.64	0.48	0.15**
	(0.49)	(0.48)	(0.50)	(0.00)
Firm Size	5888.06	5706.69	6261.87	-555.18**
	(4453.50)	(4475.86)	(4383.98)	(0.00)
Female-Friendly Firm	0.74	0.74	0.74	0.00
	(0.44)	(0.44)	(0.44)	(0.90)
Top 100 MBA Firm	0.34	0.32	0.38	-0.06**
	(0.47)	(0.47)	(0.48)	(0.00)
P&L Role	0.60	0.60	0.60	0.00
	(0.49)	(0.49)	(0.49)	(0.60)

Notes: Summary statistics reported for full sample, male students only and female students only. Standard deviations unless otherwise denoted are reported in parentheses. The last column reports the male-female difference. The p-value of the two sample t-test is reported in parentheses. Data in panel A. Academic Outcomes come from the school administrative dataset. Data at the person level. Data in panel B. Career Outcomes come from the public LinkedIn profile dataset with the exception of (i) base compensation (imp.) and total compensation (imp.), that comes from the Glassdoor dataset, (ii) firm size that come from the LinkedIn company profile dataset, and (iii) female-friendly firm rating (1-5), that come from the InHerSight.com dataset. Data at the person-year level. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Summary Statistics by Job Title (Survey Data)

	(1) Manager	(2) Director	(3) VP	(4) SVP	(5) C-Level
Firm Hierarchy (1=Lowest,5=Highest)	2.74	3.28	3.62	4.01	4.61
	(0.73)	(0.58)	(0.62)	(0.61)	(0.57)
Total Reports	14.40	26.77	137.78	296.06	554.73
	(42.57)	(66.08)	(355.20)	(986.17)	(1508.10)
Weekly Hours	53.43	51.93	59.31	55.87	56.04
	(11.74)	(11.73)	(10.83)	(14.09)	(10.30)
Total Compensation	185314.86	242184.96	344097.26	392922.02	345059.71
	(86019.66)	(96963.00)	(134468.00)	(132811.37)	(147157.58)
Observations	683	820	915	536	495

Notes: Data from survey. Sample includes students of the graduating classes 2000-2018, excluding 2009

Table A4: Gender Gap in Senior Management: Pooled Sample (Detailed Controls)

	(1)	(2)	(3)
Female	-0.128***	-0.126***	-0.122***
	(0.0138)	(0.0138)	(0.0138)
Pre-MBA Experience		-0.000402	0.000716
		(0.00378)	(0.00376)
Pre-MBA Management Experience		0.00520	0.0135
		(0.0177)	(0.0176)
Pre-MBA Senior-Level Management Experience		0.0971***	0.0880***
		(0.0206)	(0.0205)
Top 20 Undergrad		-0.00638	-0.00947
		(0.0147)	(0.0147)
Worked in P&L Role		-0.0215	-0.0132
		(0.0163)	(0.0163)
Pre-MBA Firm Size		-0.000000502	-0.000000508
		(0.00000150)	(0.00000150)
Worked in Finance			0.0738***
			(0.0179)
Worked in Consulting			0.0339
			(0.0209)
Worked in Consumer Goods			-0.0219
			(0.0230)
Worked in Healthcare			-0.00831
			(0.0282)
Worked in Tech			-0.00525
			(0.0182)
Worked in Other Industries			0.00637
			(0.0180)
Class x Year FE	Yes	Yes	Yes
Mean	0.490	0.490	0.490
Mean (Male)	0.543	0.543	0.543
R^2	0.219	0.224	0.229
N	27309	27309	27309

Notes: We present the coefficients from regressing a dummy for holding a senior management position on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and pre-MBA characteristics using the pooled sample. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Randomization Test (Caeyers and Fafchamps, 2021)

	(1) Female Top 20 Undergrad	(2) Female Senior Manager	(3) Female Finance
Female share	0.211	0.142	-0.333
	(0.236)	(0.132)	(0.282)
R^2	0.0297	0.0124	0.0157
N	1758	1640	1546
Class FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (A2) pooling together all years since graduation (Caeyers and Fafchamps, 2021). The dependent variable is being a female student from a top 20 undergraduate institution in Column (1), being a female student with senior managerial experience in Column (2), being a female student with experience in finance in Column (3). Estimations include the gender dummy and class fixed effect. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: F-Test for Joint Significance

	(1) Female Share
Female	-0.00169
	(0.0104)
Female & Attended Top-20 Undergrad	0.000905
	(0.00250)
Female & Worked as Senior Manager	0.00118
	(0.00276)
Female & Worked in Finance	-0.00321
	(0.00224)
R^2	0.519
N	4365
F-test	0.559
Class FE	Yes

Notes: We present the coefficients from regressing female share on the female dummy and the three variables that predict the probability of becoming senior manager (coming from a top 20 undergraduate institution, having experience as senior manager, having worked in finance). We test for the joint significance of these coefficients. Estimations include class fixed effect. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Section-Level Characteristics Correlated with Higher Proportion of Female Peers

Section Characteristics	(1) Full Sample	(2) Mean for Above Median Female Share Sections	(3) Mean for Below Median Female Share Sections	(4) Coefficient	(5) p-value
Share of Section with ...					
Pre-MBA Years of Experience	5.024	5.062	4.982	0.001	0.975
Any Management Experience	0.405	0.413	0.396	0.114	0.015**
Any Senior-Level Management Experience	0.131	0.135	0.126	0.196	0.021**
Entrepreneur	0.024	0.024	0.024	-0.199	0.275
Finance	0.338	0.318	0.361	-0.145	0.021**
Consulting	0.173	0.178	0.168	-0.128	0.043**
Consumer Goods	0.117	0.125	0.109	0.141	0.063*
Healthcare	0.056	0.051	0.061	-0.062	0.582
Tech	0.201	0.193	0.209	-0.031	0.551
Other Industries	0.374	0.388	0.360	0.120	0.027**
Less than 200 Employees	0.223	0.220	0.226	-0.038	0.508
200-4,999 Employees	0.220	0.217	0.223	0.064	0.292
5000+ Employees	0.727	0.728	0.726	-0.108	0.062*
Worked in Female-Friendly Firm	0.746	0.736	0.757	-0.025	0.631
Worked in a P&L Role	0.429	0.446	0.410	0.148	0.003***
US Locality	0.772	0.775	0.770	0.157	0.034**
Top 20 Undergrad	0.249	0.251	0.247	0.098	0.227
White	0.433	0.439	0.427	0.267	0.007***
Foreign	0.308	0.295	0.321	-0.486	0.000***
Observations	148	77	71	148	148

All results based on all sections in the baseline sample for the graduating classes 2000-2018, excluding 2009. Class of 2009 is excluded. Column 4 reports the coefficient from a regression of female share in the section on the variable in the row header and a constant term. Column 4 reports the associated p-value (based on heteroskedasticity-robust standard errors). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Effect of Female Peers on Likelihood of Holding a Senior Management Position by Year Since Graduation

	(1) Year 1	(2) Year 3	(3) Year 5	(4) Year 7	(5) Year 9	(6) Year 11	(7) Year 13	(8) Year 15
Female share × Male	0.0765	0.0331	-0.370*	-0.0164	0.166	0.235	0.340	-0.196
	(0.139)	(0.209)	(0.199)	(0.246)	(0.227)	(0.225)	(0.221)	(0.221)
Female share × Female	0.300	0.754***	0.686**	1.251***	1.127***	0.367	1.338***	1.140***
	(0.211)	(0.272)	(0.291)	(0.339)	(0.407)	(0.376)	(0.457)	(0.412)
p-value Male vs. Female	0.398	0.035	0.001	0.002	0.023	0.746	0.033	0.001
Female Mean	0.137	0.214	0.363	0.460	0.546	0.581	0.591	0.593
Male Mean	0.228	0.328	0.501	0.634	0.685	0.726	0.741	0.741
R^2	0.065	0.056	0.049	0.051	0.041	0.037	0.042	0.042
N	4972	4568	4236	3700	3212	2641	2302	1660

Notes: We present the coefficients for men and women from estimating equation (1) separately for each year since graduation. Estimates include class fixed effect, an indicator for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with female dummy. Finally, it includes a series of section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Effect of Female Peers on Likelihood of Ever Holding a Senior Management Position by Year Since Graduation

	(1) Year 1	(2) Year 3	(3) Year 5	(4) Year 7	(5) Year 9	(6) Year 11	(7) Year 13	(8) Year 15
Female share × Male	0.0501	0.00394	-0.250	-0.00562	0.0989	0.101	0.124	0.130
	(0.141)	(0.205)	(0.207)	(0.240)	(0.196)	(0.163)	(0.169)	(0.242)
Female share × Female	0.313	0.927***	0.763**	1.110***	1.189***	0.750***	0.768***	0.679**
	(0.208)	(0.258)	(0.307)	(0.372)	(0.354)	(0.268)	(0.282)	(0.260)
p-value Male vs. Female	0.304	0.002	0.002	0.008	0.007	0.034	0.037	0.070
Female Mean	0.138	0.227	0.406	0.546	0.658	0.723	0.753	0.788
Male Mean	0.230	0.340	0.538	0.702	0.796	0.853	0.887	0.903
R^2	0.062	0.054	0.050	0.053	0.050	0.047	0.058	0.057
N	5001	4595	4270	3741	3263	2696	2359	1711

Notes: We present the coefficients for men and women from estimating equation (1) separately for each year since graduation. Refer to Table A8 for a full list of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Effect of Female Peers on Senior Management by Seniority Level

	(1) Director and VP	(2) SVP	(3) C-Suite
Female share × Male	0.107	-0.105	0.110
	(0.137)	(0.121)	(0.0782)
Female share × Female	0.733***	0.0941	-0.112
	(0.185)	(0.149)	(0.0872)
p-value Male vs. Female	0.002	0.302	0.078
Female Mean	0.304	0.069	0.037
Male Mean	0.372	0.120	0.062
R^2	.0709	.058	.0358
N	51440	51440	51440
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Effect of Female Peers on Senior Management and Firm Size

	Senior Manager		
	(1) Firm with Less than 200 Employees	(2) Firm with 200 to 4,999 Employees	(3) Firm with More than 5,000 Employees
Female share × Female	0.171*	0.0258	0.495**
	(0.0878)	(0.161)	(0.219)
Female Mean	0.064	0.089	0.240
Male Mean	0.106	0.115	0.313
R^2	0.035	0.037	0.089
N	45169	45169	45169
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Effect of Female Peers on Senior Management and Firm Compensation

	Senior Manager			
	(1) Firm with Total Compensation Above Median	(2) Firm with Total Compensation Below Median	(3) Firm with Senior Total Compensation Above Median	(4) Firm with Senior Total Compensation Below Median
Female share × Female	0.541	0.244	0.454	0.331*
	(0.494)	(0.286)	(0.442)	(0.195)
Female Mean	0.178	0.061	0.189	0.049
Male Mean	0.309	0.081	0.334	0.057
R^2	0.239	0.127	0.276	0.083
N	34459	34459	27582	27582
Class x Year x Female FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Effects of Female Peers on Firm Size

	(1) Number of Employees	(2) Less than 200 Employees	(3) 200 to 4,999 Employees	(4) More than 5,000 Employees
Female share × Female	-1673.1	-0.0449	-0.0246	0.0589
	(2178.0)	(0.164)	(0.176)	(0.246)
Female Mean	5975.751	0.158	0.147	0.678
Male Mean	5484.606	0.183	0.171	0.641
R^2	0.051	0.024	0.023	0.043
N	44759	45171	45171	45171
Class x Year x Female FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Effect of Female Peers on Firm Compensation

	(1) Base Annual Compensation	(2) Senior Manager Base Annual Compensation	(3) Total Annual Compensation	(4) Senior Manager Total Annual Compensation	(5) Gender Gap in Total Annual Compensation	(6) Gender Gap in Senior Manager Total Annual Compensation
Female share × Female	-8635.1	-73758.4**	-639392.9	-9251981.2	-0.0565	-1.015
	(28711.1)	(36692.5)	(425867.0)	(5823970.3)	(0.137)	(0.679)
Female Mean	1.00e+05	1.78e+05	1.53e+05	3.62e+05	0.118	0.087
Male Mean	1.06e+05	1.82e+05	2.07e+05	9.80e+05	0.147	0.121
R^2	0.098	0.103	0.013	0.015	0.067	0.040
N	34461	27582	34461	27582	28086	23066
Class x Year x Female FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Effect of Female Peers on P & L Functions

	Senior Manager	
	(1) P & L Functions	(2) P & L Functions
Female share × Female	0.461**	0.106
	(0.213)	(0.221)
Female Mean	0.264	0.598
Male Mean	0.363	0.612
R^2	0.108	0.026
N	43860	43860
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2011-2018. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Effect of Female Peers on Probability of Senior Management in Male and Female Dominated Industries

	Senior Manager		
	(1) Male Dominated Industries	(2) Female Dominated Industries	(3) Male Dominated Industries
Female share × Female	0.605**	-0.0269	0.243
	(0.243)	(0.107)	(0.260)
Female Mean	0.201	0.074	0.483
Male Mean	0.344	0.072	0.626
R^2	0.097	0.033	0.037
N	45389	45389	45391
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Estimates include class fixed effects, year fixed effects class-by-year fixed effects, indicators for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. We also control for the following section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Effect of Female Peers on Senior Management: Additional Controls

	Senior Manager	
	(1)	(2)
	Main Result	Additional Controls
Female share × Female	0.822***	0.622***
	(0.204)	(0.237)
Female Mean	0.391	0.391
Male Mean	0.534	0.534
R^2	0.173	0.260
N	51440	30257
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for full set of control variables in Column (1). Additional controls in Column (2) include number of employees in the firm and total average annual compensation at the firm, plus all their interactions with the gender dummy. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A18: Match Statistics

Data Source	Units	Unit Match Rate	Unit-Year Observations	Unit-Year Match Rate
A. Individuals – Cohorts 2000-2008, 2010-2018				
All 2-Year Full-Time MBAs	8509	1.000		
LinkedIn Profiles	6556	0.770	66514	1.000
LinkedIn Profiles (US Locality Only)	5098	0.599	52160	0.784
B. Firms – Cohorts 2000-2008, 2010-2018				
All Firms Listed on LinkedIn Profiles	6590	1.000	52160	1.000
LinkedIn Company Profiles	4397	0.667	44742	0.858
Glassdoor	2868	0.435	35493	0.680
InHerSight	1399	0.212	28168	0.540
FairyGodBoss	434	0.066	19305	0.370
Women On Board	587	0.089	16531	0.317
C. Administrative Data – Cohorts 2011-2018				
All 2-Year Full-Time MBAs	3425	1.000		
LinkedIn Profiles	2783	0.813	14875	1.000
LinkedIn Profiles (US Locality Only)	2097	0.612	10992	0.739
D. Survey Data – Cohorts 2000-2008, 2010-2015				
Full Sample	328	1.000	4246	1.000
2-Year Full-Time MBA	160	0.488	2195	0.517

We report the match rate across the different datasets in our sample. Panel A describes the main analysis sample of individuals who graduated between 2000 and 2018, excluding 2009. In Panel B, we present the match rate across the different firm datasets for our sample. In Panel C, we report the number of observations for the administrative data and the number of matched observations to the LinkedIn data. In Panel D, we report the number of observations in the survey data.

Table A19: Missing Data

	(1) Matched to LinkedIn Profile 2000-2010	(2) Matched to LinkedIn Profile (US Sample Only) 2000-2010	(3) Matched to LinkedIn Profile 2011-2018	(4) Matched to LinkedIn Profile (US Sample Only) 2011-2018	(5) Matched to LinkedIn Company Profile	(6) Matched to Glassdoor	(7) Matched to InHerSight
Female share × Female	-0.166	0.0976	-0.171	-0.0644	-0.135	-0.126	-0.215
	(0.227)	(0.344)	(0.128)	(0.109)	(0.0937)	(0.135)	(0.162)
R^2	0.0228	0.0104	0.553	0.342	0.256	0.121	0.0936
N	4512	4512	2888	2888	55984	55984	55984
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes	Yes
Class x Year x Female FE	No	No	No	No	Yes	Yes	Yes
Level of Observations	Person	Person	Person	Person	Person-Year	Person-Year	Person-Year

We present the coefficients for women from estimating equation (1) pooling together all years since graduation. The dependent variable in each column is a dummy if the individual is matched to the specified dataset. Estimates include gender dummy, class and year fixed effects. Because this analysis requires microdata and we do not have individual data for the full census of MBA graduates prior to 2011, we use the alumni directory records as a proxy for the sample universe in Columns (1) and (2). That is, missing dummy equals 1 if in the alumni directory records and 0 otherwise. In Columns (3) and (4), we use the matched LinkedIn and administrative data to conduct the analysis for the 2011-2018 cohorts. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Effect of Female Peers on Senior Management: Pre-MBA

	(1) Year -4	(2) Year -3	(3) Year -2
Female share × Female	0.0616	-0.0902	0.0218
	(0.102)	(0.0831)	(0.0855)
Female Mean	0.075	0.095	0.106
Male Mean	0.083	0.110	0.123
R^2	0.572	0.764	0.868
N	4669	4710	4716

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Effect of Female Peers on Senior Management: Pooled Sample

	(1) Senior-Level Manager	(2) Senior-Level Manager	(3) Senior-Level Manager	(4) Senior-Level Manager
Female share × Male	0.0315	-0.0885	-0.0903	-0.102
	(0.115)	(0.0916)	(0.0917)	(0.0937)
Female share × Female	0.822***	0.674***	0.673***	0.681***
	(0.204)	(0.182)	(0.182)	(0.183)
p-value Male vs. Female	0.000	0.000	0.000	0.000
Female Mean	0.391	0.391	0.391	0.391
Male Mean	0.534	0.534	0.534	0.534
R^2	0.173	0.166	0.166	0.172
N	51440	51440	51440	51440
Class x Year x Female FE	Yes	Yes	Yes	Yes
Stratification Controls	Yes	No	Yes	Yes
Pre-MBA Characteristics Controls	Yes	No	No	Yes
Section-level Controls	Yes	No	No	No

Notes: We present the coefficients for men and women from estimating equation (1) pooling together all years since graduation. Estimates in Column (1) include class fixed effects, year fixed effects class-by-year fixed effects, as well as their interactions with a female dummy. Estimates in Column (2) include the controls in Column (1) plus an indicator for having attended a top 20 U.S. undergraduate university based on U.S. News Ranking, as well as its interaction with a female dummy. Estimates in Column (3) include the controls in Column (2) plus indicators for having any senior management experience, and having worked in finance, as well as their interactions with a female dummy. Finally, estimates in Column (4) include the controls in Column (3) plus a series of section-level characteristics: share of section with management experience, senior-level management experience, worked in finance, worked in consulting, worked in other industries, worked in a P&L role, white, and foreign. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A22: Effect of Female Peers on Senior Management: Robustness Checks

	Senior Manager							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Main Result	Alternative Non-Employment Definition	Balanced Sample	Without Outliers	With Only $\leq 25^{th}$ vs $\geq 75^{th}$ Female Share	With Founders	Sample with Industry Data	Sample with Female-Friendly Firm Data
Female share × Female	0.822***	0.728***	1.125***	0.663**	0.443*	0.671***	0.698***	0.535*
	(0.204)	(0.208)	(0.292)	(0.260)	(0.244)	(0.228)	(0.244)	(0.295)
Female Mean	0.391	0.382	0.462	0.393	0.380	0.391	0.394	0.350
Male Mean	0.534	0.531	0.606	0.535	0.505	0.534	0.533	0.488
R^2	0.173	0.169	0.129	0.173	0.184	0.189	0.193	0.247
N	51440	52083	24340	50400	26054	51440	45389	28093
Class x Year x Female FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. In all columns, the outcome variable is the probability of holding a senior management position. Each coefficient is the result of a separate estimation from a series of alternative sample restrictions. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Effect of Female Peers on Senior Management: Clustering at Alternative Levels

	Senior Manager		
	(1) Clustered at Section Level (Main Result)	(2) Clustered at Class Level	(3) Two Way Clustering at Individual and Year Level
Female share × Female	0.822***	0.822***	0.822***
	(0.204)	(0.195)	(0.254)
Female Mean	0.391	0.391	0.391
Male Mean	0.534	0.534	0.534
R^2	0.173	0.173	0.173
N	51440	51440	51440
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level in Column (1) and at the class level in Column(2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A24: Effect of Female Peers on Senior Management: Pooled Sample (Logit)

	(1) Senior-Level Manager (Linear)	(2) Senior-Level Manager (Logit)
Female share × Male	0.0315	0.831
	(0.115)	(1.408)
Female share × Female	0.822***	5.328**
	(0.204)	(2.504)
p-value Male vs. Female	0.000	0.088
Female Mean	0.391	0.391
Male Female	0.534	0.534
R^2	0.173	
N	51440	51429
Class x Year x Female FE	Yes	Yes

Notes: In Column (1), we present the coefficients for women from estimating equation (1) pooling together all years since graduation. In Column (2), we show the coefficients for women from the corresponding logistic specification. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2015. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A25: Effect of Female Peers on Employment and Career Breaks

	(1) Employed	(2) Cumulative Months In Non-Employment	(3) Senior-Level Manager (Unconditional)	(4) Senior-Level Manager (Conditional)
Female share × Female	-0.0154	4.502	0.822***	0.841***
	(0.0487)	(4.795)	(0.204)	(0.206)
Female Mean	0.985	1.707	0.391	0.403
Male Mean	0.995	0.633	0.534	0.542
R^2	0.025	0.077	0.173	0.183
N	49991	51482	51440	50428
Class x Year x Female FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A26: Effect of Female Peers on Likelihood of Holding Any Management Position

	(1) Any-Level Manager
Female share × Female	0.229
	(0.182)
Female Mean	0.744
Male Mean	0.767
R^2	0.058
N	51440
Class x Year x Female FE	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A27: Effect of Female Peers on Entrepreneurship

	(1) Entrepreneurs
Female share × Female	-0.184
	(0.111)
Female Mean	0.035
Male Mean	0.040
R^2	0.019
N	51451
Class x Year x Female FE	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A28: Effect of Female Peers on Senior Management by Industries and Types of Firms

	(1) P-value of the Difference
External vs Internal Promotions to Senior Manager	0.195
Male-Dominated vs Female-Dominated Industries	0.0297
Female-Friendly vs Non Female-Friendly Firms	0.0141
Male-Dom. and Fem.-Friendly vs Male-Dom. and Non Fem.-Friendly	0.0942
Female-Dom. and Fem.-Friendly vs Female-Dom. and Non Fem.-Friendly	0.0735
Less than 200 Employees vs 200 to 4,999 Employees	0.472
Less than 200 Employees vs More than 5,000 Employees	0.218
200 to 4,999 Employees vs More than 5,000 Employees	0.0881
Total Compensation Above vs Below Median	0.656
Total Senior Compensation Above vs Below Median	0.809

Notes: We present the p-values from the tests of pairwise differences across the two specifications. All estimates are obtained from running equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A29: Effect of Female Peers on Industry Choice

	(1) Finance	(2) Consulting	(3) Consumer Goods	(4) Healthcare	(5) Technology	(6) Other
Female share × Female	0.285	-0.215	-0.120	0.329**	0.0555	-0.175
	(0.208)	(0.159)	(0.191)	(0.146)	(0.261)	(0.254)
Female Mean	0.162	0.125	0.192	0.077	0.208	0.273
Male Mean	0.276	0.136	0.117	0.078	0.247	0.223
R^2	0.062	0.057	0.025	0.016	0.027	0.021
N	45391	45391	45391	45391	45391	45391
Class x Year x Female FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A30: Effect of Female Peers on Male Dominated Industries

	Senior Manager	
	(1) Restricted to Male Dominated Industries	(2) Restricted to Female Dominated Industries
Female share × Female	0.821**	0.0821
	(0.373)	(0.371)
Female Mean	0.415	0.303
Male Mean	0.549	0.476
R^2	0.219	0.248
N	26339	8199
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Data at the individual level. Outcomes defined as ever entering in each of the listed industries in the first 15 years post graduation. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A31: Female-Friendly Firms versus Non-Female Friendly Firms

	Female-Friendly	Non-Female-Friendly	Difference
Number of Employees	4660.63	4813.23	152.61
	(4185.63)	(4159.29)	
Total Annual Compensation	147309.33	261589.84	114280.51
	(559259.52)	(3533693.33)	
Paid Maternity Leave	11.84	11.39	-0.45
	(6.31)	(7.57)	
% Female Board Members	30.68	26.16	-4.53**
	(10.36)	(10.28)	
Observations	786	601	1387

Notes: Summary statistics reported for female-friendly and non female-friendly firms. Standard deviations unless otherwise denoted are reported in parentheses. The last column reports the difference. Data at the firm level. Summary statistics on firm size, firm average compensation, weeks of paid maternity leave, and percentage of female board members. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A32: Effect of Female Peers on Senior Manager in Female-Friendly Firms

	Female-Friendly Firm		Firm with Gender Equal Opportunities		Firm with Work Schedule Flexibility		Firm with Professional Enrichment	
	(1) Above Median	(2) Below Median	(3) Above Median	(4) Below Median	(5) Above Median	(6) Below Median	(7) Above Median	(8) Below Median
Female share × Female	1.243***	-0.468	0.613*	0.162	1.158***	-0.382	1.000**	-0.225
	(0.394)	(0.402)	(0.341)	(0.385)	(0.411)	(0.423)	(0.407)	(0.438)
Female Mean	0.161	0.118	0.151	0.128	0.157	0.122	0.152	0.127
Male Mean	0.238	0.186	0.215	0.209	0.241	0.184	0.237	0.188
R^2	0.167	0.242	0.158	0.222	0.165	0.238	0.166	0.228
N	28505	28505	28505	28505	28503	28503	28488	28488
Class x Year x Female FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Firm with Fair Compensation		Firm with Family Friendliness		Firm with Workplace Culture	
	(1) Above Median	(2) Below Median	(3) Above Median	(4) Below Median	(5) Above Median	(6) Below Median
Female share × Female	0.328	0.448	1.097***	-0.322	0.815**	-0.0393
	(0.340)	(0.277)	(0.394)	(0.413)	(0.373)	(0.383)
Female Mean	0.187	0.092	0.159	0.120	0.125	0.154
Male Mean	0.288	0.137	0.243	0.182	0.198	0.226
R^2	0.235	0.187	0.163	0.241	0.122	0.233
N	28488	28488	28473	28473	28488	28488
Class x Year x Female FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A33: Effect of Female Peers on Female-Friendly Firms: Components

	(1) Female-Friendly Rating	(2) Gender Equal Opportunities	(3) Work Schedule Flexibility	(4) Professional Enrichment	(5) Fair Compensation	(6) Family Friendliness	(7) Workplace Culture
Female share × Female	0.857	0.631	0.809	0.613	-0.291	0.702	0.469
	(0.915)	(0.635)	(0.918)	(0.916)	(0.673)	(0.913)	(0.779)
Female Mean	0.532	0.524	0.521	0.519	0.599	0.532	0.485
Male Mean	0.542	0.437	0.546	0.542	0.666	0.550	0.497
R^2	0.123	0.106	0.121	0.118	0.106	0.121	0.093
N	28505	28505	28503	28488	28488	28473	28488
Class x Year x Female FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A34: Effect of Female Peers on Probability of Senior Management Conditioned on the Type of Firm

	Senior Manager	
	(1) Female-Friendly Firms	(2) Non Female-Friendly Firms
Female share × Female	1.190***	-0.418
	(0.418)	(0.831)
Female Mean	0.303	0.252
Male Mean	0.439	0.407
R^2	0.314	0.504
N	20893	7612
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Data at the individual level. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A35: Effect of Female Peers on Probability of Senior Management in Female-Friendly Firms (Restricted to Big Firms)

	Senior Manager		
	(1) Female-Friendly Firms	(2) Non Female-Friendly Firms	(3) Female-Friendly Firms
Female share × Female	1.158***	-0.546	1.018
	(0.416)	(0.436)	(0.895)
Female Mean	0.164	0.123	0.503
Male Mean	0.246	0.186	0.532
R^2	0.176	0.260	0.151
N	23352	23352	23352
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Data at the individual level. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A36: Effect of Female Peers on Probability of Senior Management in Female Friendly Firms (Restricted to Male Dominated Industries)

	Senior Manager (Restricted to Male Dominated Industries)	
	(1) Female-Friendly Firms	(2) Non Female-Friendly Firms
Female share × Female	1.407**	0.0990
	(0.562)	(0.405)
Female Mean	0.239	0.089
Male Mean	0.294	0.136
R^2	0.205	0.248
N	16887	16887
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes graduating classes 2000-2018, excluding 2009. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A37: Effect of Female Peers on Probability of Senior Management in Male Dominated Industries and Female Friendly Firms

	Senior Manager in Male Dominated Industry	
	(1)	(2)
	Female-Friendly Firm	Non Female-Friendly Firm
Female share × Female	0.722*	-0.200
	(0.368)	(0.279)
Female Mean	0.115	0.043
Male Mean	0.179	0.083
R^2	0.127	0.175
N	28505	28505
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Data at the individual level. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A38: Effect of Female Peers on Probability of Senior Management in Female Dominated Industries and Female Friendly Firms

	Senior Manager in Female Dominated Industry	
	(1)	(2)
	Female-Friendly Firm	Non Female-Friendly Firm
Female share × Female	0.297*	-0.346
	(0.160)	(0.302)
Female Mean	0.027	0.059
Male Mean	0.035	0.085
R^2	0.090	0.255
N	28505	28505
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Data at the individual level. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A39: Referral Effect: Probability of Entering the Same Firm

	(1)
Same Section × Both Males	0.000059
	(0.000473)
Same Section × Both Males × Female-Friendly Firm	-0.000215
	(0.000660)
Same Section × Mixed Gender	-0.000644
	(0.000487)
Same Section × Mixed Gender × Female-Friendly Firm	0.000428
	(0.000707)
Same Section × Both Females	-0.000118
	(0.000946)
Same Section × Both Females × Female-Friendly Firm	0.002810**
	(0.001430)
p-value Both Male vs. Both Female	.055300
Female Mean	.006549
Male Mean	.006420
R^2	.050743
N	7,623,733
Class x Year FE	Yes
Firm FE	Yes

Notes: We present the coefficients for men and women from estimating equation (2) pooling together all years since graduation. Estimates include class fixed effects, year fixed effects, class-by-year fixed effects, and firm fixed effects. Dataset created by matching each MBA graduate (from graduating classes 2000-2018, excluding 2009) with all possible classmates of the same graduating year. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A40: Effect of Female Peers on GPA during MBA

	(1) Overall GPA	(2) Fraction Finance Classes
Female share × Female	-0.103	-0.0246
	(0.112)	(0.0443)
Mean	3.519	0.154
SD	0.273	0.105
R^2	0.0666	0.156
N	3425	3425

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2011-2018. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A41: Effect of Female Peers on Core GPA during MBA by Field of Study

	(1) Accounting	(2) Decision	(3) KPPI	(4) MECN
Female share × Female	-0.00907	-0.306	0.435	0.0201
	(0.340)	(0.248)	(0.286)	(0.295)
Mean	3.359	3.404	3.435	3.376
SD	0.597	0.565	0.534	0.599
R^2	0.0632	0.0513	0.0338	0.0450
N	1915	2024	1285	2105

	(1) Management	(2) Marketing	(3) MORS	(4) Operations	(5) Strategy
Female share × Female	-0.917*	0.181	0.172	-0.395	0.668**
	(0.451)	(0.262)	(0.194)	(0.311)	(0.292)
Mean	3.366	3.451	3.425	3.400	3.400
SD	0.616	0.546	0.515	0.595	0.602
R^2	0.0700	0.0441	0.0312	0.0503	0.0470
N	1663	2274	2518	2154	855

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2011-2018. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A42: Effect of Female Peers on Compensation

	(1) Total Annual Compensation (Imp.)	(2) Base Annual Compensation (Imp.)	(3) Non-Base Annual Compensation (Imp.)
Female share × Female	75.26	-11.32	86.57**
	(69.89)	(33.10)	(42.66)
Female Mean	117.482	90.861	26.621
Male Mean	178.865	117.206	61.658
R^2	0.173	0.263	0.105
N	26567	26567	26567
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A43: Effect of Female Peers on Compensation

	(1) Total Annual Compensation (Imp.)	(2) Base Annual Compensation (Imp.)	(3) Non-Base Annual Compensation (Imp.)
Female share × Female	43.15	-22.23	65.39*
	(55.21)	(25.71)	(36.81)
Female Mean	117.482	90.861	26.621
Male Mean	178.865	117.206	61.658
R^2	0.400	0.598	0.243
N	26567	26567	26567
Class x Year x Female FE	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Outcome variable in thousands of dollars. Sample includes students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A44: Match Rate by Class

Class	All	Males	Females
2000	0.776	0.811	0.701
2001	0.756	0.774	0.732
2002	0.748	0.808	0.623
2003	0.685	0.714	0.620
2004	0.825	0.831	0.810
2005	0.862	0.868	0.846
2006	0.878	0.864	0.906
2007	0.820	0.835	0.775
2008	0.837	0.865	0.780
2010	0.805	0.844	0.739
2011	0.769	0.773	0.761
2012	0.681	0.695	0.653
2013	0.710	0.690	0.741
2014	0.904	0.920	0.876
2015	0.752	0.785	0.696
2016	0.682	0.696	0.659
2017	0.651	0.653	0.649
2018	0.734	0.735	0.734
All	0.770	0.788	0.735

Notes: We report the matching rate by class and gender of the LinkedIn profiles for the sample of individuals who graduated between 2000 and 2018, excluding 2009.

Table A45: Coverage Rate of Alumni Directory, 2000-2010 Records

	Overall		Male		Female	
	N	Non-Missing Share	N	Non-Missing Share	N	Non-Missing Share
Admin Data	4720	1.000	3210	1.000	1503	1.000
Alumni Directory	4532	0.960	3132	0.976	1380	0.918

Notes: We report the coverage rate of the alumni directory compared to the total number of graduates from official administrative statistics. Sample includes students of the graduating classes 2000-2018, excluding 2009.

Table A46: Coverage Rate of Alumni Directory Records by Class, 2000-2010

	Overall		Male		Female	
	N	Non-Missing Share	N	Non-Missing Share	N	Non-Missing Share
Cohort 2000						
Admin Data	486	1.000	328	1.000	157	1.000
Alumni Directory	453	0.932	313	0.954	138	0.879
Cohort 2001						
Admin Data	479	1.000	323	1.000	153	1.000
Alumni Directory	443	0.925	306	0.947	136	0.889
Cohort 2002						
Admin Data	465	1.000	317	1.000	146	1.000
Alumni Directory	440	0.946	307	0.968	130	0.890
Cohort 2003						
Admin Data	460	1.000	318	1.000	142	1.000
Alumni Directory	438	0.952	309	0.972	127	0.894
Cohort 2004						
Admin Data	469	1.000	326	1.000	142	1.000
Alumni Directory	453	0.966	316	0.969	135	0.951
Cohort 2005						
Admin Data	456	1.000	326	1.000	130	1.000
Alumni Directory	449	0.985	320	0.982	126	0.969
Cohort 2006						
Admin Data	476	1.000	337	1.000	139	1.000
Alumni Directory	463	0.973	319	0.947	142	1.022
Cohort 2007						
Admin Data	479	1.000	328	1.000	151	1.000
Alumni Directory	470	0.981	327	0.997	139	0.921
Cohort 2008						
Admin Data	478	1.000	319	1.000	159	1.000
Alumni Directory	464	0.971	323	1.013	141	0.887
Cohort 2010						
Admin Data	472	1.000	288	1.000	184	1.000
Alumni Directory	459	0.972	292	1.014	166	0.902

Notes: We report the coverage rate of the alumni directory compared to the total number of graduates from official administrative statistics by class year. Sample includes students of the graduating classes 2000-2018, excluding 2009.

Table A47: Gender Gap in Senior Management: Pooled Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.128***	-0.126***	-0.122***	-0.120***	-0.111***	-0.0959***
	(0.0138)	(0.0138)	(0.0138)	(0.0138)	(0.0136)	(0.0137)
Class x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Characteristics		Yes	Yes	Yes	Yes	Yes
Pre-MBA Industry FE			Yes	Yes	Yes	Yes
Cummulative Months of Career Break				Yes	Yes	Yes
Post-MBA Characteristics					Yes	Yes
Post-MBA Industry FE						Yes
Mean	0.490	0.490	0.490	0.490	0.490	0.490
Mean (Male)	0.543	0.543	0.543	0.543	0.543	0.543
R^2	0.219	0.224	0.229	0.230	0.251	0.272
N	27309	27309	27309	27309	27309	27309

Notes: We present coefficient estimates from regressing a dummy for holding a senior management position on a female dummy, class fixed effects, year fixed effects, class interacted with year fixed effects, and additional controls. Pre-MBA characteristics include years of experience, top 20 undergraduate institution, management experience, P&L experience. Cumulative months of career break inferred based on the employment dates listed on the online profiles. Post-MBA controls such as experience, firm size, PL role. Sample of all individual-year observations for students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A48: Gender Gap in Senior Management: Pooled Sample (Includes Additional Firm Characteristics)

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.114***	-0.111***	-0.110***	-0.110***	-0.118***	-0.110***
	(0.0249)	(0.0246)	(0.0245)	(0.0245)	(0.0240)	(0.0239)
Class x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Characteristics		Yes	Yes	Yes	Yes	Yes
Pre-MBA Industry FE			Yes	Yes	Yes	Yes
Cummulative Months of Career Break				Yes	Yes	Yes
Post-MBA Characteristics					Yes	Yes
Post-MBA Industry FE						Yes
Mean	0.419	0.419	0.419	0.419	0.419	0.419
Mean (Male)	0.473	0.473	0.473	0.473	0.473	0.473
R^2	0.314	0.329	0.335	0.335	0.382	0.395
N	6625	6625	6625	6625	6625	6625

Notes: We present coefficient estimates from regressing a dummy for holding a senior management position on a female dummy, the same variables as in Table A47, as well as additional firm characteristics from Glassdoor and InHerSight. Sample of all individual-year observations for students of the graduating classes 2000-2018, excluding 2009. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A49: Gender Gap in Senior Management: Linked Administrative Sample, 2011-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.0932***	-0.0867***	-0.0747***	-0.0758***	-0.0571**	-0.0473*	-0.0262
	(0.0254)	(0.0255)	(0.0256)	(0.0257)	(0.0242)	(0.0249)	(0.0266)
Class x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Characteristics		Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Industry FE			Yes	Yes	Yes	Yes	Yes
Cumulative Months of Career Break				Yes	Yes	Yes	Yes
Post-MBA Characteristics					Yes	Yes	Yes
Post-MBA Industry FE						Yes	Yes
GMAT, % Finance Classes, Kellogg GPA							Yes
Mean	0.316	0.316	0.316	0.316	0.316	0.316	0.316
R^2	0.171	0.191	0.214	0.214	0.288	0.317	0.323
N	4669	4669	4669	4669	4669	4669	4669

Notes: We present coefficient estimates from regressing a dummy for holding a senior management position on a female dummy, the same variables as in Table A47, as well as academic performance (GPA), GMAT scores, and share of finance classes taken. Sample of all individual-year observations for students of the graduating classes 2011-2018. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A50: Gender Gap in Senior Management: Pooled Sample (Survey Data)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.132**	-0.133**	-0.126**	-0.109*	-0.123*	-0.118*	-0.104
	(0.0536)	(0.0536)	(0.0551)	(0.0582)	(0.0653)	(0.0656)	(0.0644)
Weekly Hours		0.000373	0.000323	0.000247	0.000294	-0.0000968	-0.000150
		(0.00214)	(0.00215)	(0.00213)	(0.00213)	(0.00211)	(0.00210)
Children			0.0130	0.0205	0.0188	0.0147	0.00477
			(0.0227)	(0.0241)	(0.0242)	(0.0246)	(0.0244)
Pre-School Child Care Responsibilities (%)				-0.00156	-0.00184	-0.00189	-0.00126
				(0.00161)	(0.00178)	(0.00179)	(0.00174)
Employment Gap after First Child (Weeks)					0.00171	0.00245	0.00166
					(0.00381)	(0.00384)	(0.00375)
Ambition to be CEO in 5 Years						0.0764	0.0773
						(0.0494)	(0.0491)
Class x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience and Industry Controls	No	No	No	No	No	No	Yes
Mean	0.693	0.693	0.693	0.693	0.693	0.693	0.693
R^2	0.108	0.108	0.109	0.111	0.112	0.117	0.144
N	3025	3025	3025	3025	3025	3025	3025

Notes: We present coefficient estimates from regressing a dummy for holding a senior management position on a female dummy, the same variables as in Table A47, as well as additional controls from the survey data including weekly hours worked, number of children, pre-school child care responsibilities, employment gap after childbirth, and ambition to become CEO in 5 years. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A51: Gender Differences in Manager Characteristics (Senior Managers Only)

	Males	Females	Difference
Female-Friendly Firm	0.70	0.73	-0.03**
	(0.46)	(0.44)	(0.00)
Male Dominated Industry	0.83	0.73	0.10**
	(0.38)	(0.44)	(0.00)
Firm Size	4903.25	4998.76	-95.51
	(4514.14)	(4465.30)	(0.17)
Total Employee Reviews	1491.55	1598.67	-107.12*
	(3596.17)	(3589.31)	(0.09)
Female Share of Employee Reviews	0.38	0.47	-0.08**
	(0.22)	(0.22)	(0.00)
Female Sr. Manager Share	0.30	0.37	-0.07**
	(0.21)	(0.23)	(0.00)
Average Firm Total Compensation (000's)	195.80	161.97	33.83
	(1785.55)	(569.85)	(0.22)
Average Firm Total Compensation for Senior Managers (000's)	961.81	321.62	640.20
	(26197.71)	(442.71)	(0.14)
Gender Gap in Firm Total Compensation (%)	0.15	0.10	0.06**
	(0.41)	(0.58)	(0.00)
Gender Gap in Firm Total Compensation for Senior Managers (%)	0.09	0.03	0.07**
	(1.20)	(0.71)	(0.00)
P&L Responsibilities	0.65	0.65	-0.00
	(0.48)	(0.48)	(1.00)
Observations	18333	6376	24709

Notes: We report the summary statistics by gender for the sample of senior managers. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A52: Gender Differences in Manager Characteristics (Senior Managers Only – Survey Sample)

	Males	Females	Difference
Total Compensation	357466.80	279613.67	77853.12**
	(128130.32)	(128939.32)	(0.00)
Weekly Hours	56.99	54.02	2.98**
	(12.15)	(15.43)	(0.00)
Total Reports	164.42	35.65	128.77**
	(770.14)	(85.43)	(0.00)
Firm Size	18477.98	21300.13	-2822.14*
	(20510.81)	(19482.12)	(0.03)
P & L Responsibilties	0.53	0.29	0.25**
	(0.50)	(0.45)	(0.00)
Ambition to be CEO in 5 Years	0.45	0.12	0.34**
	(0.50)	(0.32)	(0.00)
Asked for Raise	0.43	0.44	-0.01
	(0.49)	(0.50)	(0.68)
Asked for Raise Successfully	1.00	0.93	0.07**
	(0.05)	(0.26)	(0.00)
Asked for Promotion	0.39	0.40	-0.01
	(0.49)	(0.49)	(0.77)
Asked for Promotion Successfully	0.93	0.99	-0.06**
	(0.26)	(0.09)	(0.01)
Observations	888	312	1200

Notes: We report the summary statistics by gender for the sample of senior managers using survey data. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A53: Effect of Female Peers on Number of Years in Senior Management Positions

	(1) Total Number of Years as Senior Manager Positions
Female share × Female	10.84***
	(2.880)
Female Mean	4.968
Male Mean	7.040
R^2	0.306
N	52094
Class x Year x Female FE	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A54: Effect of Female Peers on Years to First Senior Management Position

	(1) Years to First Senior Manager Position	(2) Total Positions as Senior Manager
Female share × Female	-8.375***	1.362*
	(2.871)	(0.766)
Female Mean	4.940	1.126
Male Mean	4.359	1.562
R^2	0.088	0.314
N	3313	5087
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A55: Effect of Female Peers on External vs Internal Promotions

	Senior Manager	
	(1) External Promotion	(2) Internal Promotion
Female share × Female	0.591***	0.303**
	(0.153)	(0.152)
Female Mean	0.269	0.132
Male Mean	0.343	0.197
R^2	0.212	0.037
N	50506	50506
Class x Year x Female FE	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Data at the individual level. Outcomes defined as ever entering in each of the listed industries in the first 15 years post graduation. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A56: Effect of Female Peers on Senior Manager in Female-Friendly Firms: Alternative Measures

	Female-Friendly Firm (FGB)		Firm with Paid Maternity Leave		Firm with % Female Board Members	
	(1) Above Median	(2) Below Median	(3) Above Median	(4) Below Median	(5) Above Median	(6) Below Median
Female share × Female	0.487*	0.417	0.807**	0.428***	0.668**	0.154
	(0.248)	(0.448)	(0.316)	(0.162)	(0.329)	(0.173)
Female Mean	0.084	0.152	0.245	0.062	0.263	0.070
Male Mean	0.128	0.223	0.341	0.095	0.346	0.145
R^2	0.092	0.189	0.177	0.068	0.143	0.085
N	18050	18050	19279	19279	16525	16525
Class x Year x Female FE	Yes	Yes	Yes	Yes	Yes	Yes

	Firm with Gender Pay Gap		Firm with Gender Pay Gap for Sr. Managers	
	(1) Above Median	(2) Below Median	(3) Above Median	(4) Below Median
Female share × Female	0.700*	0.0845	0.551*	0.236
	(0.420)	(0.305)	(0.309)	(0.450)
Female Mean	0.140	0.098	0.106	0.132
Male Mean	0.253	0.138	0.212	0.178
R^2	0.223	0.129	0.200	0.173
N	28457	28457	23133	23133
Class x Year x Female FE	Yes	Yes	Yes	Yes

Notes: We present the coefficients for women from estimating equation (1) pooling together all years since graduation. Refer to Table 3 for the full set of control variables. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A57: Gender Differences in Total Compensation (Imputed)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-89.76***	-90.23***	-88.78***	-87.85***	-89.18***	-70.64***	-57.23***
	(12.08)	(12.63)	(12.75)	(12.65)	(12.55)	(10.53)	(8.907)
Class x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Characteristics		Yes	Yes	Yes	Yes	Yes	Yes
Pre-MBA Industry FE			Yes	Yes	Yes	Yes	Yes
Cummulative Months of Career Break				Yes	Yes	Yes	Yes
Post-MBA Characteristics					Yes	Yes	Yes
Post-MBA Industry FE						Yes	Yes
Current Broad Managerial Category							Yes
Mean	234.3	234.3	234.3	234.3	234.3	234.3	234.3
Mean (Male)	268.3	268.3	268.3	268.3	268.3	268.3	268.3
R^2	0.0414	0.0441	0.0470	0.0476	0.0643	0.117	0.183
N	16769	16769	16769	16769	16769	16769	16769

We present coefficient estimates from regressing total annual compensation on a female dummy and the same variables as in Table A47. Sample of all individual-year observations for students of the graduating classes 2011-2018. Observations are restricted to the first fifteen years since graduation. Standard errors clustered at the section level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A58: Gender Gap in Compensation: Pooled Sample (Survey Data)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.220***	-0.218***	-0.199**	-0.126	-0.127	-0.118	-0.118
	(0.0815)	(0.0802)	(0.0804)	(0.0765)	(0.0920)	(0.0912)	(0.0912)
Weekly Hours		0.00636**	0.00618*	0.00582*	0.00582*	0.00515	0.00515
		(0.00322)	(0.00324)	(0.00325)	(0.00324)	(0.00326)	(0.00326)
Children			0.0386	0.0719**	0.0718**	0.0636*	0.0636*
			(0.0330)	(0.0339)	(0.0346)	(0.0353)	(0.0353)
Pre-School Child Care Responsibilities (%)				-0.00659**	-0.00660**	-0.00669**	-0.00669**
				(0.00254)	(0.00270)	(0.00268)	(0.00268)
Employment Gap after First Child (Weeks)					0.0000783	0.00138	0.00138
					(0.00671)	(0.00668)	(0.00668)
Ambition to be CEO in 5 Years						0.138*	0.138*
						(0.0760)	(0.0760)
Class x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience and Industry Controls	No	No	No	No	No	No	Yes
Mean	12.38	12.38	12.38	12.38	12.38	12.38	12.38
R^2	0.112	0.125	0.129	0.151	0.151	0.159	0.159
N	2913	2913	2913	2913	2913	2913	2913

Notes: We present coefficient estimates from regressing total annual compensation on a female dummy, the same variables as in Table A47, as well as additional controls from the survey data including weekly hours worked, number of children, pre-school child care responsibilities, employment gap after childbirth, and ambition to become CEO in 5 years. Sample includes students of the graduating classes 2000-2018, excluding 2009. Standard errors clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.